

# SPARSE MODELS AND METHODS FOR OPTIMAL INSTRUMENTS WITH AN APPLICATION TO EMINENT DOMAIN

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**ABSTRACT.** We develop results for the use of Lasso and Post-Lasso methods to form first-stage predictions and estimate optimal instruments in linear instrumental variables (IV) models with many instruments,  $p$ . Our results apply even when  $p$  is much larger than the sample size,  $n$ . We show that the IV estimator based on using Lasso or Post-Lasso in the first stage is root- $n$  consistent and asymptotically normal when the first-stage is approximately sparse; i.e. when the conditional expectation of the endogenous variables given the instruments can be well-approximated by a relatively small set of variables whose identities may be unknown. We also show the estimator is semi-parametrically efficient when the structural error is homoscedastic. Notably our results allow for imperfect model selection, and do not rely upon the unrealistic "beta-min" conditions that are widely used to establish validity of inference following model selection. In simulation experiments, the Lasso-based IV estimator with a data-driven penalty performs well compared to recently advocated many-instrument-robust procedures. In an empirical example dealing with the effect of judicial eminent domain decisions on economic outcomes, the Lasso-based IV estimator outperforms an intuitive benchmark.

Optimal instruments are conditional expectations. In developing the IV results, we establish a series of new results for Lasso and Post-Lasso estimators of nonparametric conditional expectation functions which are of independent theoretical and practical interest. We construct a modification of Lasso designed to deal with non-Gaussian, heteroscedastic disturbances which uses a data-weighted  $\ell_1$ -penalty function. By innovatively using moderate deviation theory for self-normalized sums, we provide convergence rates for the resulting Lasso and Post-Lasso estimators that are as sharp as the corresponding rates in the homoscedastic Gaussian case under the condition that  $\log p = o(n^{1/3})$ . We also provide a data-driven method for choosing the penalty level that must be specified in obtaining Lasso and Post-Lasso estimates and establish its asymptotic validity under non-Gaussian, heteroscedastic disturbances.

**Key Words:** Inference on a low-dimensional parameter after model selection, imperfect model selection, instrumental variables, Lasso, post-Lasso, data-driven penalty, heteroscedasticity, non-Gaussian errors, moderate deviations for self-normalized sums

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*Date:* First version: June 2009, this version September 11, 2012. This is a revision of an October 2010 ArXiv/CEMMAP paper with the same title. Preliminary results of this paper were first presented at Chernozhukov's invited Cowles Foundation lecture at the Northern American meetings of the Econometric society in June of 2009. We thank seminar participants at Brown, Columbia, Hebrew University, Tel Aviv University, Harvard-MIT, the Dutch Econometric Study Group, Fuqua School of Business, NYU, and New Economic School, for helpful comments. We also thank Denis Chetverikov, JB Doyle, and Joonhwan Lee for thorough reading of this paper and very useful comments.

## 1. INTRODUCTION

Instrumental variables (IV) techniques are widely used in applied economic research. While these methods provide a useful tool for identifying structural effects of interest, their application often results in imprecise inference. One way to improve the precision of instrumental variables estimators is to use many instruments or to try to approximate the optimal instruments as in Amemiya (1974), Chamberlain (1987), and Newey (1990). Estimation of optimal instruments will generally be done nonparametrically and thus implicitly makes use of many constructed instruments such as polynomials. The promised improvement in efficiency is appealing, but IV estimators based on many instruments may have poor properties. See, for example, Bekker (1994), Chao and Swanson (2005), Hansen, Hausman, and Newey (2008), and Hausman, Newey, Woutersen, Chao, and Swanson (2009) which propose solutions for this problem based on “many-instrument” asymptotics.<sup>1</sup>

In this paper, we contribute to the literature on IV estimation with many instruments by considering the use of Lasso and Post-Lasso for estimating the first-stage regression of endogenous variables on the instruments. Lasso is a widely used method that acts both as an estimator of regression functions and as a model selection device. Lasso solves for regression coefficients by minimizing the sum of the usual least squares objective function and a penalty for model size through the sum of the absolute values of the coefficients. The resulting Lasso estimator selects instruments and estimates the first-stage regression coefficients via a shrinkage procedure. The Post-Lasso estimator discards the Lasso coefficient estimates and uses the data-dependent set of instruments selected by Lasso to refit the first stage regression via OLS to alleviate Lasso’s shrinkage bias. For theoretical and simulation evidence regarding Lasso’s performance, see Bai and Ng (2008, 2009a), Bickel, Ritov, and Tsybakov (2009), Bunea, Tsybakov, and Wegkamp (2006, 2007a, 2007b), Candès and Tao (2007), Huang, Horowitz, and Wei (2010), Knight (2008), Koltchinskii (2009), Lounici (2008), Lounici, Pontil, Tsybakov, and van de Geer (2010), Meinshausen and Yu (2009), Rosenbaum and Tsybakov (2008), Tibshirani (1996), van de Geer (2008), Wainwright (2009), Zhang and Huang (2008), Belloni and Chernozhukov (2012), and Bühlmann and van de Geer (2011) among many others. See Belloni and Chernozhukov (2012) for analogous results on Post-Lasso.

Using Lasso-based methods to form first-stage predictions in IV estimation provides a practical approach to obtaining the efficiency gains from using optimal instruments while dampening the problems associated with many instruments. We show that Lasso-based procedures produce first-stage predictions that provide good approximations to the optimal instruments even

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<sup>1</sup>It is important to note that the precise definition of “many-instrument” is  $p \propto n$  with  $p < n$  where  $p$  is the number of instruments and  $n$  is the sample size. The current paper allows for this case and also for “very many-instrument” asymptotics where  $p \gg n$ .

when the number of available instruments is much larger than the sample size when the first-stage is approximately sparse – that is, when there exists a relatively small set of important instruments whose identities are unknown that well-approximate the conditional expectation of the endogenous variables given the instruments. Under approximate sparsity, estimating the first-stage relationship using Lasso-based procedures produces IV estimators that are root- $n$  consistent and asymptotically normal. The IV estimator with Lasso-based first stage also achieves the semi-parametric efficiency bound under the additional condition that structural errors are homoscedastic. Our results allow imperfect model selection and do not impose “beta-min” conditions that restrict the minimum allowable magnitude of the coefficients on relevant regressors. We also provide a consistent asymptotic variance estimator. Thus, our results generalize the IV procedure of Newey (1990) and Hahn (2002) based on conventional series approximation of the optimal instruments. Our results also generalize Bickel, Ritov, and Tsybakov (2009) by providing inference and confidence sets for the second-stage IV estimator based on Lasso or Post-Lasso estimates of the first-stage predictions. To our knowledge, our result is the first to verify root- $n$  consistency and asymptotic normality of an estimator for a low-dimensional structural parameter in a high-dimensional setting without imposing the very restrictive “beta-min” condition.<sup>2</sup> Our results also remain valid in the presence of heteroscedasticity and thus provide a useful complement to existing approaches in the many instrument literature which often rely on homoscedasticity and may be inconsistent in the presence of heteroscedasticity; see Hausman, Newey, Woutersen, Chao, and Swanson (2009) for a notable exception that allows for heteroscedasticity and gives additional discussion.

Instrument selection procedures complement existing/traditional methods that are meant to be robust to many-instruments but are not a universal solution to the many instruments problem. The good performance of instrument selection procedures relies on approximate sparsity. Unlike traditional IV methods, instrument selection procedures do not require the identity of these “important” variables to be known *a priori* as the identity of these instruments will be estimated from the data. This flexibility comes with the cost that instrument selection will tend not to work well when the first-stage is not approximately sparse. When approximate sparsity breaks down, instrument selection procedures may select too few or no instruments or may select too many instruments. Two scenarios where this failure is likely to occur are the weak-instrument case; e.g. Staiger and Stock (1997), Andrews, Moreira, and Stock (2006), Andrews and Stock (2005), Moreira (2003), Kleibergen (2002), and Kleibergen (2005); and the many-weak-instrument case; e.g. Bekker (1994), Chao and Swanson (2005), Hansen, Hausman, and Newey (2008), and

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<sup>2</sup>The “beta-min” condition requires the relevant coefficients in the regression to be separated from zero by a factor that exceeds the potential estimation error. This condition implies the identities of the relevant regressors may be perfectly determined. There is a large body of theoretical work that uses such a condition and thus implicitly assumes that the resulting post-model selection estimator is the same as the oracle estimator that knows the identities of the relevant regressors. See Bühlmann and van de Geer (2011) for the discussion of the “beta-min” condition and the theoretical role it plays in obtaining “oracle” results.

Hausman, Newey, Woutersen, Chao, and Swanson (2009). We consider two modifications of our basic procedure aimed at alleviating these concerns. In Section 4, we present a sup-score testing procedure that is related to Anderson and Rubin (1949) and Staiger and Stock (1997) but is better suited to cases with very many instruments; and we consider a split sample IV estimator in Section 5 which combines instrument selection via Lasso with the sample-splitting method of Angrist and Krueger (1995). While these two procedures are steps toward addressing weak identification concerns with very many instruments, further exploration of the interplay between weak-instrument or many-weak-instrument methods and variable selection would be an interesting avenue for additional research.

Our paper also contributes to the growing literature on Lasso-based methods by providing results for Lasso-based estimators of nonparametric conditional expectations. We consider a modified Lasso estimator with penalty weights designed to deal with non-Gaussianity and heteroscedastic errors. This new construction allows us to innovatively use the results of moderate deviation theory for self-normalized sums of Jing, Shao, and Wang (2003) to provide convergence rates for Lasso and Post-Lasso. The derived convergence rates are as sharp as in the homoscedastic Gaussian case under the weak condition that the log of the number of regressors  $p$  is small relative to  $n^{1/3}$ , i.e.  $\log p = o(n^{1/3})$ . Our construction generalizes the standard Lasso estimator of Tibshirani (1996) and allows us to generalize the Lasso results of Bickel, Ritov, and Tsybakov (2009) and Post-Lasso results of Belloni and Chernozhukov (2012) both of which assume homoscedasticity and Gaussianity. The construction as well as theoretical results are important for applied economic analysis where researchers are concerned about heteroscedasticity and non-Gaussianity in their data. We also provide a data-driven method for choosing the penalty that must be specified to obtain Lasso and Post-Lasso estimates, and we establish its asymptotic validity allowing for non-Gaussian, heteroscedastic disturbances. Ours is the first paper to provide such a data-driven penalty which was previously not available even in the Gaussian case.<sup>3</sup> These results are of independent interest in a variety of theoretical and applied settings.

We illustrate the performance of Lasso-based IV through simulation experiments. In these experiments, we find that a feasible Lasso-based procedure that uses our data-driven penalty performs well across a range of simulation designs where sparsity is a reasonable approximation. In terms of estimation risk, it outperforms the estimator of Fuller (1977) (FULL),<sup>4</sup> which is robust to many instruments (e.g. Hansen, Hausman, and Newey, 2008), except in a design where sparsity breaks down and the sample size is large relative to the number of instruments. In terms of size of 5% level tests, the Lasso-based IV estimator performs comparably to or better

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<sup>3</sup>One exception is the work of Belloni, Chernozhukov, and Wang (2011b) which considers square-root-Lasso estimators and shows that their use allows for pivotal penalty choices. Those results strongly rely on homoscedasticity.

<sup>4</sup>Note that this procedure is only applicable when the number of instruments  $p$  is less than the sample size  $n$ . As mentioned earlier, procedures developed in this paper allow for  $p$  to be much larger  $n$ .

than FULL in all cases we consider. Overall, the simulation results are in line with the theory and favorable to the proposed Lasso-based IV procedures.

Finally, we demonstrate the potential gains of the Lasso-based procedure in an application where there are many available instruments among which there is not a clear *a priori* way to decide which instruments to use. We look at the effect of judicial decisions at the federal circuit court level regarding the government's exercise of eminent domain on house prices and state-level GDP as in Chen and Yeh (2010). We follow the identification strategy of Chen and Yeh (2010) who use the random assignment of judges to three judge panels that are then assigned to eminent domain cases to justify using the demographic characteristics of the judges on the realized panels as instruments for their decision. This strategy produces a situation in which there are many potential instruments in that all possible sets of characteristics of the three judge panel are valid instruments. We find that the Lasso-based estimates using the data-dependent penalty produce much larger first-stage Wald-statistics and generally have smaller estimated second stage standard errors than estimates obtained using the baseline instruments of Chen and Yeh (2010).

**Relationship to econometric literature on variable selection and shrinkage.** The idea of instrument selection goes back to Kloek and Mennes (1960) and Amemiya (1966) who searched among principal components to approximate the optimal instruments. Related ideas appear in dynamic factor models as in Bai and Ng (2010), Kapetanios and Marcellino (2010), and Kapetanios, Khalaf, and Marcellino (2011). Factor analysis differs from our approach though principal components, factors, ridge fits, and other functions of the instruments could be considered among the set of potential instruments to select from.<sup>5</sup>

There are several other papers that explore the use of modern variable selection methods in econometrics, including some papers that apply these procedures to IV estimation. Bai and Ng (2009b) consider an approach to instrument selection that is closely related to ours based on boosting. The latter method is distinct from Lasso, cf. Bühlmann (2006), but it also does not rely on knowing the identity of the most important instruments. They show through simulation examples that instrument selection via boosting works well in the designs they consider but do not provide formal results. Bai and Ng (2009b) also expressly mention the idea of using the Lasso method for instrument selection, though they focus their analysis on the boosting method. Our paper complements their analysis by providing a formal set of conditions under which Lasso variable selection will provide good first-stage predictions and providing theoretical estimation and inference results for the resulting IV estimator. One of our theoretical results for the IV estimator is also sufficiently general to cover the use of any other first-stage variable selection procedure, including boosting, that satisfies a set of provided rate conditions. Caner

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<sup>5</sup>Approximate sparsity should be understood to be relative to a given structure defined by the set of instruments considered. Allowing for principle components or ridge fits among the potential regressors considerably expands the applicability of the approximately sparse framework.

(2009) considers estimation by penalizing the GMM criterion function by the  $\ell_\gamma$ -norm of the coefficients for  $0 < \gamma < 1$ . The analysis of Caner (2009) assumes that the number of parameters  $p$  is fixed in relation to the sample size, and so it is complementary to our approach where we allow  $p \rightarrow \infty$  as  $n \rightarrow \infty$ . Other uses of Lasso in econometrics include Bai and Ng (2008), Belloni, Chernozhukov, and Hansen (2011b), Brodie, Daubechies, Mol, Giannone, and Loris (2009), DeMiguel, Garlappi, Nogales, and Uppal (2009), Huang, Horowitz, and Wei (2010), Knight (2008), and others. An introductory treatment of this topic is given in Belloni and Chernozhukov (2011b), and Belloni, Chernozhukov, and Hansen (2011a) provides a review of Lasso targeted at economic applications.

Our paper is also related to other shrinkage-based approaches to dealing with many instruments. Chamberlain and Imbens (2004) considers IV estimation with many instruments using a shrinkage estimator based on putting a random coefficients structure over the first-stage coefficients in a homoscedastic setting. In a related approach, Okui (2010) considers the use of ridge regression for estimating the first-stage regression in a homoscedastic framework where the instruments may be ordered in terms of relevance. Okui (2010) derives the asymptotic distribution of the resulting IV estimator and provides a method for choosing the ridge regression smoothing parameter that minimizes the higher-order asymptotic mean-squared-error (MSE) of the IV estimator. These two approaches are related to the approach we pursue in this paper in that both use shrinkage in estimating the first-stage but differ in the shrinkage methods they use. Their results are also only supplied in the context of homoscedastic models. Donald and Newey (2001) consider a variable selection procedure that minimizes higher-order asymptotic MSE which relies on *a priori* knowledge that allows one to order the instruments in terms of instrument strength. Our use of Lasso as a variable selection technique does not require any *a priori* knowledge about the identity of the most relevant instruments and so provides a useful complement to Donald and Newey (2001) and Okui (2010). Carrasco (2012) provides an interesting approach to IV estimation with many instruments based on directly regularizing the inverse that appears in the definition of the 2SLS estimator; see also Carrasco and Tchuente Nguembu (2012). Carrasco (2012) considers three regularization schemes, including Tikhonov regularization which corresponds to ridge regression, and shows that the regularized estimators achieve the semi-parametric efficiency bound under some conditions. Carrasco (2012)'s approach implicitly uses  $\ell_2$ -norm penalization and hence differs from and complements our approach. A valuable feature of Carrasco (2012) is the provision of a data-dependent method for choosing the regularization parameter based on minimizing higher-order asymptotic MSE following Donald and Newey (2001) and Okui (2010). Finally, in work that is more recent than the present paper, Gautier and Tsybakov (2011) consider the important case where the structural equation in an instrumental variables model is itself very high-dimensional and propose a new estimation method related to the Dantzig selector and the square-root-Lasso. They also provide an interesting inference method which differs from the one we consider.

**Notation.** In what follows, we work with triangular array data  $\{(z_{i,n}, i = 1, \dots, n), n = 1, 2, 3, \dots\}$  defined on some common probability space  $(\Omega, \mathcal{A}, P)$ . Each  $z_{i,n} = (y'_{i,n}, x'_{i,n}, d'_{i,n})'$  is a vector, with components defined below in what follows, and these vectors are i.n.i.d. – independent across  $i$ , but not necessarily identically distributed. The law  $P_n$  of  $\{z_{i,n}, i = 1, \dots, n\}$  can change with  $n$ , though we do not make explicit use of  $P_n$ . Thus, all parameters that characterize the distribution of  $\{z_{i,n}, i = 1, \dots, n\}$  are implicitly indexed by the sample size  $n$ , but we omit the index  $n$  in what follows to simplify notation. We use triangular array asymptotics to better capture some finite-sample phenomena and to retain the robustness of conclusions to perturbations of the data-generating process. We also use the following empirical process notation,  $\mathbb{E}_n[f] := \mathbb{E}_n[f(z_i)] := \sum_{i=1}^n f(z_i)/n$ , and  $\mathbb{G}_n(f) := \sum_{i=1}^n (f(z_i) - \mathbb{E}[f(z_i)])/\sqrt{n}$ . Since we want to deal with i.n.i.d. data, we also introduce the average expectation operator:  $\bar{\mathbb{E}}[f] := \mathbb{E}\mathbb{E}_n[f] = \mathbb{E}\mathbb{E}_n[f(z_i)] = \sum_{i=1}^n \mathbb{E}[f(z_i)]/n$ . The  $\ell_2$ -norm is denoted by  $\|\cdot\|_2$ , and the  $\ell_0$ -norm,  $\|\cdot\|_0$ , denotes the number of non-zero components of a vector. We use  $\|\cdot\|_\infty$  to denote the maximal element of a vector. The empirical  $L^2(\mathbb{P}_n)$  norm of a random variable  $W_i$  is defined as  $\|W_i\|_{2,n} := \sqrt{\mathbb{E}_n[W_i^2]}$ . When the empirical  $L^2(\mathbb{P}_n)$  norm is applied to regressors  $f_1, \dots, f_p$  and a vector  $\delta \in \mathbb{R}^p$ ,  $\|f'_i \delta\|_{2,n}$ , it is called the prediction norm. Given a vector  $\delta \in \mathbb{R}^p$  and a set of indices  $T \subset \{1, \dots, p\}$ , we denote by  $\delta_T$  the vector in which  $\delta_{Tj} = \delta_j$  if  $j \in T$ ,  $\delta_{Tj} = 0$  if  $j \notin T$ . We also denote  $T^c := \{1, 2, \dots, p\} \setminus T$ . We use the notation  $(a)_+ = \max\{a, 0\}$ ,  $a \vee b = \max\{a, b\}$  and  $a \wedge b = \min\{a, b\}$ . We also use the notation  $a \lesssim b$  to denote  $a \leq cb$  for some constant  $c > 0$  that does not depend on  $n$ ; and  $a \lesssim_P b$  to denote  $a = O_P(b)$ . For an event  $E$ , we say that  $E \rightarrow 1$  when  $E$  occurs with probability approaching one as  $n$  grows. We say  $X_n =_d Y_n + o_P(1)$  to mean that  $X_n$  has the same distribution as  $Y_n$  up to a term  $o_P(1)$  that vanishes in probability.

## 2. SPARSE MODELS AND METHODS FOR OPTIMAL INSTRUMENTAL VARIABLES

In this section of the paper, we present the model and provide an overview of the main results. Sections 3 and 4 provide a technical presentation that includes a set of sufficient regularity conditions, discusses their plausibility, and establishes the main formal results of the paper.

**2.1. The IV Model and Statement of The Problem.** The model is  $y_i = d'_i \alpha_0 + \epsilon_i$  where  $\alpha_0$  denotes the true value of a vector-valued parameter  $\alpha$ .  $y_i$  is the response variable, and  $d_i$  is a finite  $k_d$ -vector of variables whose first  $k_e$  elements contain endogenous variables. The disturbance  $\epsilon_i$  obeys for all  $i$  (and  $n$ ):

$$\mathbb{E}[\epsilon_i | x_i] = 0,$$

where  $x_i$  is a  $k_x$ -vector of instrumental variables.

As a motivation, suppose that the structural disturbance is conditionally homoscedastic, namely, for all  $i$ ,  $\mathbb{E}[\epsilon_i^2 | x_i] = \sigma^2$ . Given a  $k_d$ -vector of instruments  $A(x_i)$ , the standard IV estimator of  $\alpha_0$  is given by  $\hat{\alpha} = (\mathbb{E}_n[A(x_i)d'_i])^{-1}\mathbb{E}_n[A(x_i)y_i]$ , where  $\{(x_i, d_i, y_i), i = 1, \dots, n\}$  is an i.i.d.

sample from the IV model above. For a given  $A(x_i)$ ,  $\sqrt{n}(\hat{\alpha} - \alpha_0) =_d N(0, Q_0^{-1}\Omega_0Q_0^{-1}) + o_P(1)$ , where  $Q_0 = \bar{E}[A(x_i)d_i']$  and  $\Omega_0 = \sigma^2\bar{E}[A(x_i)A(x_i)']$  under standard conditions. Setting  $A(x_i) = D(x_i) = E[d_i|x_i]$  minimizes the asymptotic variance which becomes

$$\Lambda^* = \sigma^2\{\bar{E}[D(x_i)D(x_i)']\}^{-1},$$

the semi-parametric efficiency bound for estimating  $\alpha_0$ ; see Amemiya (1974), Chamberlain (1987), and Newey (1990). In practice, the optimal instrument  $D(x_i)$  is an unknown function and has to be estimated. In what follows, we investigate the use of sparse methods – namely Lasso and Post-Lasso – for use in estimating the optimal instruments. The resulting IV estimator is asymptotically as efficient as the infeasible optimal IV estimator above.

Note that if  $d_i$  contains exogenous components  $w_i$ , then  $d_i = (d_{i1}, \dots, d_{ik_e}, w_i')'$  where the first  $k_e$  variables are endogenous. Since the rest of the components  $w_i$  are exogenous, they appear in  $x_i = (w_i', \tilde{x}_i')'$ . It follows that  $D_i := D(x_i) := E[d_i|x_i] = (E[d_1|x_i], \dots, E[d_{k_e}|x_i], w_i')'$ ; i.e. the estimator of  $w_i$  is simply  $w_i$ . Therefore, we discuss estimation of the conditional expectation functions:

$$D_{il} := D_l(x_i) := E[d_l|x_i], \quad l = 1, \dots, k_e.$$

In what follows, we focus on the strong instruments case which translates into the assumption that  $Q = \bar{E}[D(x_i)D(x_i)']$  has eigenvalues bounded away from zero and from above. We also present an inference procedure that remains valid in the absence of strong instruments which is related to Anderson and Rubin (1949) and Staiger and Stock (1997) but allows for  $p \gg n$ .

## 2.2. Sparse Models for Optimal Instruments and Other Conditional Expectations.

Suppose there is a very large list of instruments,

$$f_i := (f_{i1}, \dots, f_{ip})' := (f_1(x_i), \dots, f_p(x_i))',$$

to be used in estimation of conditional expectations  $D_l(x_i)$ ,  $l = 1, \dots, k_e$ , where the number of instruments  $p$  is possibly much larger than the sample size  $n$ .

For example, high-dimensional instruments  $f_i$  could arise as any combination of the following two cases. First, the list of available instruments may simply be large, in which case  $f_i = x_i$  as in e.g. Amemiya (1974) and Bekker (1994). Second, the list  $f_i$  could consist of a large number of series terms with respect to some elementary regressor vector  $x_i$ ; e.g.,  $f_i$  could be composed of B-splines, dummies, polynomials, and various interactions as in Newey (1990) or Hahn (2002) among others. We term the first example the many instrument case and the second example the many series instrument case and note that our formulation does not require us to distinguish between the two cases. We mainly use the term “series instruments” and contrast our results with those in the seminal work of Newey (1990) and Hahn (2002), though our results are not limited to canonical series regressors as in Newey (1990) and Hahn (2002). The most important feature of our approach is that by allowing  $p$  to be much larger than the sample size, we are able



to consider many more series instruments than in Newey (1990) and Hahn (2002) to approximate the optimal instruments.

The key assumption that allows effective use of this large set of instruments is sparsity. To fix ideas, consider the case where  $D_l(x_i)$  is a function of only  $s \ll n$  instruments:

$$\begin{aligned} D_l(x_i) &= f'_i \beta_{l0}, \quad l = 1, \dots, k_e, \\ \max_{1 \leq l \leq k_e} \|\beta_{l0}\|_0 &= \max_{1 \leq l \leq k_e} \sum_{j=1}^p 1\{\beta_{l0j} \neq 0\} \leq s \ll n. \end{aligned} \quad (2.1)$$

This simple sparsity model generalizes the classic parametric model of optimal instruments of Amemiya (1974) by letting the identities of the relevant instruments  $T_l = \text{support}(\beta_{l0}) = \{j \in \{1, \dots, p\} : |\beta_{l0j}| > 0\}$  be unknown.

The model given by (2.1) is unrealistic in that it presumes exact sparsity. We make no formal use of this model, but instead use a much more general approximately sparse or nonparametric model:

**Condition AS.(Approximately Sparse Optimal Instrument).** *Each optimal instrument function  $D_l(x_i)$  is well-approximated by a function of unknown  $s \geq 1$  instruments:*

$$\begin{aligned} D_l(x_i) &= f'_i \beta_{l0} + a_l(x_i), \quad l = 1, \dots, k_e, \quad k_e \text{ fixed}, \\ \max_{1 \leq l \leq k_e} \|\beta_{l0}\|_0 &\leq s = o(n), \quad \max_{1 \leq l \leq k_e} [\mathbb{E}_n a_l(x_i)^2]^{1/2} \leq c_s \lesssim_P \sqrt{s/n}. \end{aligned} \quad (2.2)$$

Condition AS is the key assumption. It requires that there are at most  $s$  terms for each endogenous variable that are able to approximate the conditional expectation function  $D_l(x_i)$  up to approximation error  $a_l(x_i)$  chosen to be no larger than the conjectured size  $\sqrt{s/n}$  of the estimation error of the infeasible estimator that knows the identity of these important variables, the “oracle estimator.” In other words, the number  $s$  is defined so that the approximation error is of the same order as the estimation error,  $\sqrt{s/n}$ , of the oracle estimator. Importantly, the assumption allows the identity

$$T_l = \text{support}(\beta_{l0})$$

to be unknown and to differ for  $l = 1, \dots, k_e$ .

For a detailed motivation and discussion of this assumption, we refer the reader to Belloni, Chernozhukov, and Hansen (2011a). Condition AS generalizes the conventional series approximation of optimal instruments in Newey (1990, 1997) and Hahn (2002) by letting the identities of the most important  $s$  series terms  $T_l$  be unknown. The rate  $\sqrt{s/n}$  generalizes the rate obtained with the optimal number  $s$  of series terms in Newey (1990) for estimating conditional expectation by not relying on knowledge of what  $s$  series terms to include. Knowing the identities of the most important series terms is unrealistic in many examples. The most important series terms need not be the first  $s$  terms, and the optimal number of series terms to consider is also unknown. Moreover, an optimal approximation could come from the combination of completely different bases e.g. by using both polynomials and B-splines.

Lasso and Post-Lasso use the data to estimate the set of the most relevant series terms in a manner that allows the resulting IV estimator to achieve good performance if a key growth condition,

$$\frac{s^2 \log^2(p \vee n)}{n} \rightarrow 0,$$

holds along with other more technical conditions. The growth condition requires the optimal instruments to be sufficiently smooth so that a small (relative to  $n$ ) number of series terms can be used to approximate them well. The use of a small set of instruments ensures that the impact of first-stage estimation on the IV estimator is asymptotically negligible. We can weaken this condition to  $s \log(p \vee n) = o(n)$  by using the sample-splitting idea from the many instruments literature.

**2.3. Lasso-Based Estimation Methods for Optimal Instruments and Other Conditional Expectation Functions.** Let us write the first-stage regression equations as

$$d_{il} = D_l(x_i) + v_{il}, \quad \mathbb{E}[v_{il}|x_i] = 0, \quad l = 1, \dots, k_e. \quad (2.3)$$

Given the sample  $\{(x_i, d_{il}, l = 1, \dots, k_e), i = 1, \dots, n\}$ , we consider estimators of the optimal instrument  $D_{il} := D_l(x_i)$  that take the form

$$\hat{D}_{il} := \hat{D}_l(x_i) = f'_i \hat{\beta}_l, \quad l = 1, \dots, k_e,$$

where  $\hat{\beta}_l$  is the Lasso or Post-Lasso estimator obtained by using  $d_{il}$  as the dependent variable and  $f_i$  as regressors.

Consider the usual least squares criterion function:

$$\hat{Q}_l(\beta) := \mathbb{E}_n[(d_{il} - f'_i \beta)^2].$$

The Lasso estimator is defined as a solution of the following optimization program:

$$\hat{\beta}_{lL} \in \arg \min_{\beta \in \mathbb{R}^p} \hat{Q}_l(\beta) + \frac{\lambda}{n} \|\hat{\Upsilon}_l \beta\|_1 \quad (2.4)$$

where  $\lambda$  is the penalty level and  $\hat{\Upsilon}_l = \text{diag}(\hat{\gamma}_{l1}, \dots, \hat{\gamma}_{lp})$  is a diagonal matrix specifying penalty loadings.

Our analysis will first employ the following “ideal” penalty loadings:

$$\hat{\Upsilon}_l^0 = \text{diag}(\hat{\gamma}_{l1}^0, \dots, \hat{\gamma}_{lp}^0), \quad \hat{\gamma}_{lj}^0 = \sqrt{\mathbb{E}_n[f_{ij}^2 v_{il}^2]}, \quad j = 1, \dots, p.$$

The ideal option is not feasible but leads to rather sharp theoretical bounds on estimation risk. This option is not feasible since  $v_{il}$  is not observed. In practice, we estimate the ideal loadings by first using conservative penalty loadings and then plugging-in the resulting estimated residuals in place of  $v_{il}$  to obtain the refined loadings. This procedure could be iterated via Algorithm A.1 stated in the appendix.

The idea behind the ideal penalty loading is to introduce self-normalization of the first-order condition of the Lasso problem by using data-dependent penalty loadings. This self-normalization allows us to apply moderate deviation theory of Jing, Shao, and Wang (2003) for self-normalized sums to bound deviations of the maximal element of the score vector

$$S_l = 2\mathbb{E}_n[(\hat{\Upsilon}_l^0)^{-1}f_i v_{il}]$$

which provides a representation of the estimation noise in the problem. Specifically, the use of self-normalized moderate deviation theory allows us to establish that

$$\mathbb{P}\left(\sqrt{n} \max_{1 \leq l \leq k_e} \|S_l\|_\infty \leq 2\Phi^{-1}(1 - \gamma/(2k_e p))\right) \geq 1 - \gamma + o(1), \quad (2.5)$$

from which we obtain sharp convergence results for the Lasso estimator under non-Gaussianity and heteroscedasticity. Without using these loadings, we may not be able to achieve the same sharp rate of convergence. It is important to emphasize that our construction of the penalty loadings for Lasso is new and differs from the canonical penalty loadings proposed in Tibshirani (1996) and Bickel, Ritov, and Tsybakov (2009). Finally, to insure the good performance of the Lasso estimator, one needs to select the penalty level  $\lambda/n$  to dominate the noise for all  $k_e$  regression problems simultaneously; i.e. the penalty level should satisfy

$$\mathbb{P}\left(\lambda/n \geq c \max_{1 \leq l \leq k_e} \|S_l\|_\infty\right) \rightarrow 1, \quad (2.6)$$

for some constant  $c > 1$ . The bound (2.5) suggests that this can be achieved by selecting

$$\lambda = c2\sqrt{n}\Phi^{-1}(1 - \gamma/(2k_e p)), \quad \text{with } \gamma \rightarrow 0, \quad \log(1/\gamma) \lesssim \log(p \vee n), \quad (2.7)$$

which implements (2.6). Our current recommendation is to set the confidence level  $\gamma = 0.1/\log(p \vee n)$  and the constant  $c = 1.1$ .<sup>6</sup>

The Post-Lasso estimator is defined as the ordinary least square regression applied to the model  $\hat{I}_l \supseteq \hat{T}_l$  where  $\hat{T}_l$  is the model selected by Lasso:

$$\hat{T}_l = \text{support}(\hat{\beta}_{lL}) = \{j \in \{1, \dots, p\} : |\hat{\beta}_{lLj}| > 0\}, \quad l = 1, \dots, k_e.$$

The set  $\hat{I}_l$  can contain additional variables not selected by Lasso, but we require the number of such variables to be similar to or smaller than the number selected by Lasso. The Post-Lasso estimator  $\hat{\beta}_{lPL}$  is

$$\hat{\beta}_{lPL} \in \arg \min_{\beta \in \mathbb{R}^p: \beta_{\hat{T}_l^c} = 0} \hat{Q}_l(\beta), \quad l = 1, \dots, k_e. \quad (2.8)$$

In words, this estimator is ordinary least squares (OLS) using only the instruments/regressors whose coefficients were estimated to be non-zero by Lasso and any additional variables the researcher feels are important despite having Lasso coefficient estimates of zero.

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<sup>6</sup>We note that there is not much room to change  $c$ . Theoretically, we require  $c > 1$ , and finite-sample experiments show that increasing  $c$  away from  $c = 1$  worsens the performance. Hence a value slightly above unity, namely  $c = 1.1$ , is our current recommendation. The simulation evidence suggests that setting  $c$  to any value near 1, including  $c = 1$ , does not impact the result noticeably.

Lasso and Post-Lasso are motivated by the desire to predict the target function well without overfitting. Clearly, the OLS estimator is not consistent for estimating the target function when  $p > n$ . Some approaches based on BIC-penalization of model size are consistent but computationally infeasible. The Lasso estimator of Tibshirani (1996) resolves these difficulties by penalizing model size through the sum of absolute parameter values. The Lasso estimator is computationally attractive because it minimizes a convex function. Moreover, under suitable conditions, this estimator achieves near-optimal rates in estimating the regression function  $D_l(x_i)$ . The estimator achieves these rates by adapting to the unknown smoothness or sparsity of  $D_l(x_i)$ . Nonetheless, the estimator has an important drawback: The regularization by the  $\ell_1$ -norm employed in (2.4) naturally lets the Lasso estimator avoid overfitting the data, but it also shrinks the estimated coefficients towards zero causing a potentially significant bias. The Post-Lasso estimator is meant to remove some of this shrinkage bias. If model selection by Lasso works perfectly – that is, if it selects exactly the “relevant” instruments – then the resulting Post-Lasso estimator is simply the standard OLS estimator using only the relevant variables. In cases where perfect selection does not occur, Post-Lasso estimates of coefficients will still tend to be less biased than Lasso. We prove the Post-Lasso estimator achieves the same rate of convergence as Lasso, which is a near-optimal rate, despite imperfect model selection by Lasso.

The introduction of self-normalization via the penalty loadings allows us to contribute to the broad Lasso literature cited in the introduction by showing that under possibly heteroscedastic and non-Gaussian errors the Lasso and Post-Lasso estimators obey the following near-oracle performance bounds:

$$\max_{1 \leq l \leq k_e} \|\widehat{D}_{il} - D_{il}\|_{2,n} \lesssim_P \sqrt{\frac{s \log(p \vee n)}{n}} \quad \text{and} \quad \max_{1 \leq l \leq k_e} \|\widehat{\beta}_l - \beta_{l0}\|_1 \lesssim_P \sqrt{\frac{s^2 \log(p \vee n)}{n}}. \quad (2.9)$$

The performance bounds in (2.9) are called near-oracle because they coincide up to a  $\sqrt{\log p}$  factor with the bounds achievable when the ideal series terms  $T_l$  for each of the  $k_e$  regressions equations in (2.2) are known. Our results extend those of Bickel, Ritov, and Tsybakov (2009) for Lasso with Gaussian errors and those of Belloni and Chernozhukov (2012) for Post-Lasso with Gaussian errors. Notably, these bounds are as sharp as the results for the Gaussian case under the weak condition  $\log p = o(n^{1/3})$ . They are also the first results in the literature that allow for data-driven choice of the penalty level.

It is also useful to contrast the rates given in (2.9) with the rates available for nonparametrically estimating conditional expectations in the series literature; see, for example, Newey (1997). Obtaining rates of convergence for series estimators relies on approximate sparsity just as our results do. Approximate sparsity in the series context is typically motivated by smoothness assumptions, but approximate sparsity is more general than typical smoothness assumptions.<sup>7</sup> The standard series approach postulates that the first  $K$  series terms are the most important for

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<sup>7</sup>See, e.g., Belloni, Chernozhukov, and Hansen (2011a) and Belloni, Chernozhukov, and Hansen (2011b) for detailed discussion of approximate sparsity.

approximating the target regression function  $D_{il}$ . The Lasso approach postulates that  $s$  terms from a large number  $p$  of terms are important but does not require knowledge of the identity of these terms or the number of terms,  $s$ , needed to approximate the target function well-enough that approximation errors are small relative to estimation error. Lasso methods estimate both the optimal number of series terms  $s$  as well as the identities of these terms and thus automatically adapt to the unknown sparsity (or smoothness) of the true optimal instrument (conditional expectation). This behavior differs sharply from standard series procedures that do not adapt to the unknown sparsity of the target function unless the number of series terms is chosen by a model selection method. Lasso-based methods may also provide enhanced approximation of the optimal instrument by allowing selection of the most important terms from a among a set of very many series terms with total number of terms  $p \gg K$  that can be much larger than the sample size.<sup>8</sup> For example, a standard series approach based on  $K$  terms will perform poorly when the terms  $m+1, m+2, \dots, m+j$  are the most important for approximating the optimal instrument for any  $K < m$ . On the other hand, lasso-based methods will find the important terms as long as  $p > m+j$  which is much less stringent than what is required in usual series approaches since  $p$  can be very large. This point can also be made using the array asymptotics where the model changes with  $n$  in such a way that the important series terms are always missed by the first  $K \rightarrow \infty$  terms. Of course, the additional flexibility allowed for by Lasso-based methods comes with a price, namely slowing the rate of convergence by  $\sqrt{\log p}$  relative to the usual series rates.

**2.4. The Instrumental Variable Estimator based on Lasso and Post-Lasso constructed Optimal Instrument.** Given Condition AS, we take advantage of the approximate sparsity by using Lasso and Post-Lasso methods to construct estimates of  $D_l(x_i)$  of the form

$$\hat{D}_l(x_i) = f'_i \hat{\beta}_l, \quad l = 1, \dots, k_e,$$

and then set

$$\hat{D}_i = (\hat{D}_1(x_i), \dots, \hat{D}_{k_e}(x_i), w'_i)'$$

The resulting IV estimator takes the form

$$\hat{\alpha} = \mathbb{E}_n[\hat{D}_i d'_i]^{-1} \mathbb{E}_n[\hat{D}_i y_i].$$

The main result of this paper is to show that, despite the possibility of  $p$  being very large, Lasso and Post-Lasso can select a set of instruments to produce estimates of the optimal instruments  $\hat{D}_i$  such that the resulting IV estimator achieves the efficiency bound asymptotically:

$$\sqrt{n}(\hat{\alpha} - \alpha_0) =_d N(0, \Lambda^*) + o_P(1).$$

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<sup>8</sup>We can allow for  $p \gg n$  for series formed with orthonormal bases with bounded components, such as trigonometric bases, but further restrictions on the number of terms apply if bounds on components of the series are allowed to increase with the sample size. For example, if we work with B-spline series terms, we can only consider  $p = o(n)$  terms.

The estimator matches the performance of the classical/standard series-based IV estimator of Newey (1990) and has additional advantages mentioned in the previous subsection. We also show that the IV estimator with Lasso-based optimal instruments continues to be root- $n$  consistent and asymptotically normal in the presence of heteroscedasticity:

$$\sqrt{n}(\hat{\alpha} - \alpha_0) =_d N(0, Q^{-1}\Omega Q^{-1}) + o_P(1), \quad (2.10)$$

where  $\Omega := \bar{\mathbb{E}}[\epsilon_i^2 D(x_i)D(x_i)']$  and  $Q := \bar{\mathbb{E}}[D(x_i)D(x_i)']$ . A consistent estimator for the asymptotic variance is

$$\hat{Q}^{-1}\hat{\Omega}\hat{Q}^{-1}, \quad \hat{\Omega} := \mathbb{E}_n[\hat{\epsilon}_i^2 \hat{D}(x_i)\hat{D}(x_i)'], \quad \hat{Q} := \mathbb{E}_n[\hat{D}(x_i)\hat{D}(x_i)'], \quad (2.11)$$

where  $\hat{\epsilon}_i := y_i - d_i'\hat{\alpha}$ ,  $i = 1, \dots, n$ . Using (2.11) we can perform robust inference.

We note that our result (2.10) for the IV estimator do not rely on the Lasso and Lasso-based procedure specifically. We provide the properties of the IV estimator for any generic sparsity-based procedure that achieves the near-oracle performance bounds (2.9).

We conclude by stressing that our result (2.10) does not rely on perfect model selection. Perfect model selection only occurs in extremely limited circumstances that are unlikely to occur in practice. We show that model selection mistakes do not affect the asymptotic distribution of the IV estimator  $\hat{\alpha}$  under mild regularity conditions. The intuition is that the model selection mistakes are sufficiently small to allow the Lasso or Post-Lasso to estimate the first stage predictions with a sufficient, near-oracle accuracy, which translates to the result above. Using analysis like that given in Belloni, Chernozhukov, and Hansen (2011b), the result (2.10) can be shown to hold over models with strong optimal instruments which are uniformly approximately sparse. We also offer an inference test procedure in Section 4.2 that remains valid in the absence of a strong optimal instrument, is robust to many weak instruments, and can be used even if  $p \gg n$ . This procedure could also be shown to be uniformly valid over a large class of models.

### 3. RESULTS ON LASSO AND POST-LASSO ESTIMATION OF CONDITIONAL EXPECTATION FUNCTIONS UNDER HETEROSCEDASTIC, NON-GAUSSIAN ERRORS

In this section, we present our main results on Lasso and Post-Lasso estimators of conditional expectation functions under non-classical assumptions and data-driven penalty choices. The problem we analyze in this section has many applications outside the IV framework of the present paper.

**3.1. Regularity Conditions for Estimating Conditional Expectations.** The key condition concerns the behavior of the empirical Gram matrix  $\mathbb{E}_n[f_i f_i']$ . This matrix is necessarily singular when  $p > n$ , so in principle it is not well-behaved. However, we only need good behavior of certain moduli of continuity of the Gram matrix. The first modulus of continuity is called the

restricted eigenvalue and is needed for Lasso. The second modulus is called the sparse eigenvalue and is needed for Post-Lasso.

In order to define the restricted eigenvalue, first define the restricted set:

$$\Delta_{C,T} = \{\delta \in \mathbb{R}^p : \|\delta_{T^c}\|_1 \leq C\|\delta_T\|_1, \delta \neq 0\}.$$

The restricted eigenvalue of a Gram matrix  $M = \mathbb{E}_n[f_i f_i']$  takes the form:

$$\kappa_C^2(M) := \min_{\delta \in \Delta_{C,T}, |T| \leq s} s \frac{\delta' M \delta}{\|\delta_T\|_1^2}. \quad (3.12)$$

This restricted eigenvalue can depend on  $n$ , but we suppress the dependence in our notation.

In making simplified asymptotic statements involving the Lasso estimator, we will invoke the following condition:

**Condition RE.** *For any  $C > 0$ , there exists a finite constant  $\kappa > 0$ , which does not depend on  $n$  but may depend on  $C$ , such that the restricted eigenvalue obeys  $\kappa_C(\mathbb{E}_n[f_i f_i']) \geq \kappa$  with probability approaching one as  $n \rightarrow \infty$ .*

The restricted eigenvalue (3.12) is a variant of the restricted eigenvalues introduced in Bickel, Ritov, and Tsybakov (2009) to analyze the properties of Lasso in the classical Gaussian regression model. Even though the minimal eigenvalue of the empirical Gram matrix  $\mathbb{E}_n[f_i f_i']$  is zero whenever  $p \geq n$ , Bickel, Ritov, and Tsybakov (2009) show that its restricted eigenvalues can be bounded away from zero. Lemmas 1 and 2 below contain sufficient conditions for this. Many other sufficient conditions are available from the literature; see Bickel, Ritov, and Tsybakov (2009). Consequently, we take restricted eigenvalues as primitive quantities and Condition RE as a primitive condition.

**Comment 3.1** (On Restricted Eigenvalues). In order to gain intuition about restricted eigenvalues, assume the exactly sparse model, in which there is no approximation error. In this model, the term  $\delta$  stands for a generic deviation between an estimator and the true parameter vector  $\beta_0$ . Thus, the restricted eigenvalue represents a modulus of continuity between a penalty-related term and the prediction norm, which allows us to derive the rate of convergence. Indeed, the restricted eigenvalue bounds the minimum change in the prediction norm induced by a deviation  $\delta$  within the restricted set  $\Delta_{C,T}$  relative to the norm of  $\delta_T$ , the deviation on the true support. Given a specific choice of the penalty level, the deviation of the estimator belongs to the restricted set, making the restricted eigenvalue relevant for deriving rates of convergence.

In order to define the sparse eigenvalues, let us define the  $m$ -sparse subset of a unit sphere as

$$\Delta(m) = \{\delta \in \mathbb{R}^p : \|\delta\|_0 \leq m, \|\delta\|_2 = 1\},$$

and also define the minimal and maximal  $m$ -sparse eigenvalue of the Gram matrix  $M = \mathbb{E}_n [f_i f_i']$  as

$$\phi_{\min}(m)(M) = \min_{\delta \in \Delta(m)} \delta' M \delta \quad \text{and} \quad \phi_{\max}(m)(M) = \max_{\delta \in \Delta(m)} \delta' M \delta.$$

To simplify asymptotic statements for Post-Lasso, we use the following condition:

**Condition SE.** *For any  $C > 0$ , there exist constants  $0 < \kappa' < \kappa'' < \infty$ , which do not depend on  $n$  but may depend on  $C$ , such that with probability approaching one, as  $n \rightarrow \infty$ ,  $\kappa' \leq \phi_{\min}(Cs)(\mathbb{E}_n[f_i f_i']) \leq \phi_{\max}(Cs)(\mathbb{E}_n[f_i f_i']) \leq \kappa''$ .*

Condition SE requires only that certain “small”  $m \times m$  submatrices of the large  $p \times p$  empirical Gram matrix are well-behaved, which is a reasonable assumption and will be sufficient for the results that follow. Condition SE implies Condition RE by the argument given in Bickel, Ritov, and Tsybakov (2009). The following lemmas show that Conditions RE and SE are plausible for both many-instrument and many series-instrument settings. We refer to Belloni and Chernozhukov (2012) for proofs; the first lemma builds upon results in Zhang and Huang (2008) and the second builds upon results in Rudelson and Vershynin (2008). The lemmas could also be derived from Rudelson and Zhou (2011).

**Lemma 1** (Plausibility of RE and SE under Many Gaussian Instruments). *Suppose  $f_i$ ,  $i = 1, \dots, n$ , are i.i.d. zero-mean Gaussian random vectors. Further suppose that the population Gram matrix  $\mathbb{E}[f_i f_i']$  has  $s \log n$ -sparse eigenvalues bounded from above and away from zero uniformly in  $n$ . Then if  $s \log n = o(n/\log p)$ , Conditions RE and SE hold.*

**Lemma 2** (Plausibility of RE and SE under Many Series Instruments). *Suppose  $f_i$ ,  $i = 1, \dots, n$ , are i.i.d. bounded zero-mean random vectors with  $\|f_i\|_\infty \leq K_B$  a.s. Further suppose that the population Gram matrix  $\mathbb{E}[f_i f_i']$  has  $s \log n$ -sparse eigenvalues bounded from above and away from zero uniformly in  $n$ . Then if  $K_B^2 s \log^2(n) \log^2(s \log n) \log(p \vee n) = o(n)$ , Conditions RE and SE hold.*

In the context of i.i.d. sampling, a standard assumption in econometric research is that the population Gram matrix  $\mathbb{E}[f_i f_i']$  has eigenvalues bounded from above and below, see e.g. Newey (1997). The lemmas above allow for this and more general behavior, requiring only that the sparse eigenvalues of the population Gram matrix  $\mathbb{E}[f_i f_i']$  are bounded from below and from above. The latter is important for allowing functions  $f_i$  to be formed as a combination of elements from different bases, e.g. a combination of B-splines with polynomials. The lemmas above further show that the good behavior of the population sparse eigenvalues translates into good behavior of empirical sparse eigenvalues under some restrictions on the growth of  $s$  in relation to the sample size  $n$ . For example, if  $p$  grows polynomially with  $n$  and the components of technical regressors are uniformly bounded, Lemma 2 holds provided  $s = o(n/\log^5 n)$ .



We also impose the following moment conditions on the reduced form errors  $v_{il}$  and regressors  $f_i$ , where we let  $\tilde{d}_{il} := d_{il} - \bar{E}[d_{il}]$ .

**Condition RF.** (i)  $\max_{l \leq k_e, j \leq p} \bar{E}[\tilde{d}_{il}^2] + \bar{E}[f_{ij}^2 \tilde{d}_{il}^2] + 1/\bar{E}[f_{ij}^2 v_{il}^2] \lesssim 1$ , (ii)  $\max_{l \leq k_e, j \leq p} \bar{E}[f_{ij}^3 v_{il}^3] \lesssim K_n$ , (iii)  $K_n^2 \log^3(p \vee n) = o(n)$  and  $s \log(p \vee n) = o(n)$ , (iv)  $\max_{i \leq n, j \leq p} f_{ij}^2 [s \log(p \vee n)]/n \rightarrow_P 0$  and  $\max_{l \leq k_e, j \leq p} |(\mathbb{E}_n - \bar{E})[f_{ij}^2 v_{il}^2]| + |(\mathbb{E}_n - \bar{E})[f_{ij}^2 \tilde{d}_{il}^2]| \rightarrow_P 0$ .

We emphasize that the conditions given above are only one possible set of sufficient conditions, which are presented in a manner that reduces the complexity of the exposition.

The following lemma shows that the population and empirical moment conditions appearing in Condition RF are plausible for both many-instrument and many series-instrument settings. Note that we say that a random variable  $g_i$  has uniformly bounded conditional moments of order  $K$  if for some positive constants  $0 < B_1 < B_2 < \infty$ :

$$B_1 \leq \mathbb{E}[|g_i|^k | x_i] \leq B_2 \text{ with probability 1, for } k = 1, \dots, K, i = 1, \dots, n.$$

**Lemma 3** (Plausibility of RF). 1. If the moments  $\bar{E}[\tilde{d}_{il}^8]$  and  $\bar{E}[v_{il}^8]$  are bounded uniformly in  $1 \leq l \leq k_e$  and in  $n$ , the regressors  $f_i$  obey  $\max_{1 \leq j \leq p} \mathbb{E}_n[f_{ij}^8] \lesssim_P 1$  and  $\max_{1 \leq i \leq n, 1 \leq j \leq p} f_{ij}^2 \frac{s \log(p \vee n)}{n} \rightarrow_P 0$ , Conditions RF(i)-(iii) imply Condition RF (iv). 2. Suppose that  $\{(f_i, \tilde{d}_{il}, v_{il}), i = 1, \dots, n\}$  are i.i.d. vectors, and that  $\tilde{d}_{il}$  and  $v_{il}$  have uniformly bounded conditional moments of order 4 uniformly in  $l = 1, \dots, k_e$ . (1) If the regressors  $f_i$  are Gaussian as in Lemma 1, Condition RF(iii) holds, and  $s \log^2(p \vee n)/n \rightarrow 0$  then Conditions RF(i),(ii) and (iv) hold. (2) If the regressors  $f_i$  have bounded entries as in Lemma 2, then Conditions RF(i),(ii) and (iv) hold under Condition RF(iii).

### 3.2. Results on Lasso and Post-Lasso for Estimating Conditional Expectations.

We consider Lasso and Post-Lasso estimators defined in equations (2.4) and (2.8) in the system of  $k_e$  nonparametric regression equations (2.3) with non-Gaussian and heteroscedastic errors. These results extend the previous results of Bickel, Ritov, and Tsybakov (2009) for Lasso and of Belloni and Chernozhukov (2012) for Post-Lasso with classical i.i.d. errors. In addition, we account for the fact that we are simultaneously estimating  $k_e$  regressions and account for the dependence of our results on  $k_e$ .

The following theorem presents the properties of Lasso. Let us call asymptotically valid any penalty loadings  $\hat{\Upsilon}_l$  that obey a.s.

$$\ell \hat{\Upsilon}_l^0 \leq \hat{\Upsilon}_l \leq u \hat{\Upsilon}_l^0, \quad (3.13)$$

with  $0 < \ell \leq 1 \leq u$  such that  $\ell \rightarrow_P 1$  and  $u \rightarrow_P u'$  with  $u' \geq 1$ . The penalty loadings constructed by Algorithm A.1 satisfy this condition.

**Theorem 1** (Rates for Lasso under Non-Gaussian and Heteroscedastic Errors). Suppose that in the regression model (2.3) Conditions AS and RF hold. Suppose the penalty level is specified as

in (2.7), and consider any asymptotically valid penalty loadings  $\hat{\Upsilon}$ , for example, penalty loadings constructed by Algorithm A.1 stated in Appendix A. Then, the Lasso estimator  $\hat{\beta}_l = \hat{\beta}_{lL}$  and the Lasso fit  $\hat{D}_{il} = f'_i \hat{\beta}_{lL}$ ,  $l = 1, \dots, k_e$ , satisfy

$$\max_{1 \leq l \leq k_e} \|\hat{D}_{il} - D_{il}\|_{2,n} \lesssim_P \frac{1}{\kappa_{\bar{C}}} \sqrt{\frac{s \log(k_e p / \gamma)}{n}} \quad \text{and} \quad \max_{1 \leq l \leq k_e} \|\hat{\beta}_l - \beta_{l0}\|_1 \lesssim_P \frac{1}{(\kappa_{\bar{C}})^2} \sqrt{\frac{s^2 \log(k_e p / \gamma)}{n}},$$

where  $\bar{C} = \max_{1 \leq l \leq k_e} \{\|\hat{\Upsilon}_l^0\|_\infty \|(\hat{\Upsilon}_l^0)^{-1}\|_\infty\} (uc + 1) / (\ell c - 1)$  and  $\kappa_{\bar{C}} = \kappa_{\bar{C}}(\mathbb{E}_n[f_i f'_i])$ .

The theorem provides a rate result for the Lasso estimator constructed specifically to deal with non-Gaussian errors and heteroscedasticity. The rate result generalizes, and is as sharp as, the rate results of Bickel, Ritov, and Tsybakov (2009) obtained for the homoscedastic Gaussian case. This generalization is important for real applications where non-Gaussianity and heteroscedasticity are ubiquitous. Note that the obtained rate is near-optimal in the sense that if we happened to know the model  $T_\ell$ , i.e. if we knew the identities of the most important variables, we would only improve the rate by the  $\log p$  factor. The theorem also shows that the data-driven penalty loadings defined in Algorithm A.1 are asymptotically valid.

The following theorem presents the properties of Post-Lasso which requires a mild assumption on the number of additional variables in the set  $\hat{I}_l$ ,  $l = 1, \dots, k_e$ . We assume that the size of these sets are not substantially larger than the model selected by Lasso, namely, a.s.

$$|\hat{I}_l \setminus \hat{T}_l| \lesssim 1 \vee |\hat{T}_l|, \quad l = 1, \dots, k_e. \quad (3.14)$$

**Theorem 2** (Rates for Post-Lasso under Non-Gaussian and Heteroscedastic Errors). *Suppose that in the regression model (2.3) Conditions AS and RF hold. Suppose the penalty level for the Lasso estimator is specified as in (2.7), that Lasso's penalty loadings  $\hat{\Upsilon}$  are asymptotically valid, and the sets of additional variables obey (3.14). Then, the Post-Lasso estimator  $\hat{\beta}_l = \hat{\beta}_{lPL}$  and the Post-Lasso fit  $\hat{D}_{il} = f'_i \hat{\beta}_{lPL}$ ,  $l = 1, \dots, k_e$ , satisfy*

$$\max_{1 \leq l \leq k_e} \|\hat{D}_{il} - D_{il}\|_{2,n} \lesssim_P \frac{\mu}{\kappa_{\bar{C}}} \sqrt{\frac{s \log(k_e p / \gamma)}{n}} \quad \text{and} \quad \max_{1 \leq l \leq k_e} \|\hat{\beta}_l - \beta_{l0}\|_1 \lesssim_P \frac{\mu^2}{(\kappa_{\bar{C}})^2} \sqrt{\frac{s^2 \log(k_e p / \gamma)}{n}},$$

where  $\mu^2 = \min_k \{\phi_{\max}(k)(\mathbb{E}_n[f_i f'_i]) / \phi_{\min}(k + s)(\mathbb{E}_n[f_i f'_i]) : k > 18\bar{C}^2 s \phi_{\max}(k)(\mathbb{E}_n[f_i f'_i]) / (\kappa_{\bar{C}})^2\}$  for  $\bar{C}$  defined in Theorem 1.

The theorem provides a rate result for the Post-Lasso estimator with non-Gaussian errors and heteroscedasticity. The rate result generalizes the results of Belloni and Chernozhukov (2012) obtained for the homoscedastic Gaussian case. The Post-Lasso achieves the same near-optimal rate of convergence as Lasso. As stressed in the introductory sections, our analysis allows Lasso to make model selection mistakes which is expected generically. We show that these model

selection mistakes are small enough to allow the Post-Lasso estimator to perform as well as Lasso.<sup>9</sup>

Rates of convergence in different norms can also be of interest in other applications. In particular, the  $\ell_2$ -rate of convergence can be derived from the rate of convergence in the prediction norm and Condition SE using a sparsity result for Lasso established in Appendix D. Below we specialize the previous theorems to the important case that Condition SE holds.

**Corollary 1** (Rates for Lasso and Post-Lasso under SE). *Under the conditions of Theorem 2 and Condition SE, the Lasso and Post-Lasso estimators satisfy*

$$\begin{aligned} \max_{1 \leq l \leq k_e} \|\widehat{D}_{il} - D_{il}\|_{2,n} &\lesssim_P \sqrt{\frac{s \log(p \vee n)}{n}}, \\ \max_{1 \leq l \leq k_e} \|\widehat{\beta}_l - \beta_{l0}\|_2 &\lesssim_P \sqrt{\frac{s \log(p \vee n)}{n}}, \quad \max_{1 \leq l \leq k_e} \|\widehat{\beta}_l - \beta_{l0}\|_1 \lesssim_P \sqrt{\frac{s^2 \log(p \vee n)}{n}}. \end{aligned}$$

The rates of convergence in the prediction norm and  $\ell_2$ -norm are faster than the rate of convergence in the  $\ell_1$ -norm which is typical of high dimensional settings.

#### 4. MAIN RESULTS ON IV ESTIMATION

In this section we present our main inferential results on instrumental variable estimators.

**4.1. The IV estimator with Lasso-based instruments.** We impose the following moment conditions on the instruments, the structural errors, and regressors.

**Condition SM.** (i) *The eigenvalues of  $Q = \bar{\mathbb{E}}[D(x_i)D(x_i)']$  are bounded uniformly from above and away from zero, uniformly in  $n$ . The conditional variance  $\mathbb{E}[\epsilon_i^2|x_i]$  is bounded uniformly from above and away from zero, uniformly in  $i$  and  $n$ . Given this assumption, without loss of generality, we normalize the instruments so that  $\bar{\mathbb{E}}[f_{ij}^2\epsilon_i^2] = 1$  for each  $1 \leq j \leq p$  and for all  $n$ . (ii) For some  $q > 2$  and  $q_\epsilon > 2$ , uniformly in  $n$ ,*

$$\max_{1 \leq j \leq p} \bar{\mathbb{E}}[|f_{ij}\epsilon_i|^3] + \bar{\mathbb{E}}[\|D_i\|_2^q |\epsilon_i|^{2q}] + \bar{\mathbb{E}}[\|D_i\|_2^q] + \bar{\mathbb{E}}[|\epsilon_i|^{q_\epsilon}] + \bar{\mathbb{E}}[\|d_i\|_2^q] \lesssim 1.$$

(iii) *In addition to  $\log^3 p = o(n)$ , the following growth conditions hold:*

$$(a) \frac{s \log(p \vee n)}{n} n^{2/q_\epsilon} \rightarrow 0 \quad (b) \frac{s^2 \log^2(p \vee n)}{n} \rightarrow 0, \quad (c) \max_{1 \leq j \leq p} \mathbb{E}_n[f_{ij}^2 \epsilon_i^2] \lesssim_P 1.$$

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<sup>9</sup>Under further conditions stated in proofs, Post-Lasso can sometimes achieve a faster rate of convergence. In special cases where perfect model selection is possible, Post-Lasso becomes the so-called oracle estimator and can completely remove the  $\log p$  factor.

**Comment 4.1.** (On Condition SM) Condition SM(i) places restrictions on the variation of the structural errors ( $\epsilon$ ) and the optimal instruments ( $D(x)$ ). The first condition about the variation in the optimal instrument guarantees that identification is strong; that is, it ensures that the conditional expectation of the endogenous variables given the instruments is a non-trivial function of the instruments. This assumption rules out non-identification in which case  $D(x)$  does not depend on  $x$  and weak-identification in which case  $D(x)$  would be local to a constant function. We present an inference procedure that remains valid without this condition in Section 4.2. The remaining restriction in Condition SM(i) requires that structural errors are boundedly heteroscedastic. Given this we make a normalization assumption on the instruments. This entails no loss of generality since this is equivalent to suitably rescaling the parameter space for coefficients  $\beta_{l0}$ ,  $l = 1, \dots, k_e$ , via an isomorphic transformation. We use this normalization to simplify notation in the proofs but do not use it in the construction of the estimators. Condition SM(ii) imposes some mild moment assumptions. Condition SM(iii) strengthens the growth requirement  $s \log p/n \rightarrow 0$  needed for estimating conditional expectations. However, the restrictiveness of Condition SM(iii)(a) rapidly decreases as the number of bounded moments of the structural error increases. Condition SM(iii)(b) indirectly requires the optimal instruments in Condition AS to be smooth enough that the number of unknown series terms  $s$  needed to approximate them well is not too large. This condition ensures that the impact of the instrument estimation on the IV estimator is asymptotically negligible. This condition can be relaxed using the sample-splitting method.

The following lemma shows that the moment assumptions in Condition SM (iii) are plausible for both many-instrument and many series-instrument settings.

**Lemma 4** (Plausibility of SM(iii)). *Suppose that the structural disturbance  $\epsilon_i$  has uniformly bounded conditional moments of order 4 uniformly in  $n$  and that  $s^2 \log^2(p \vee n) = o(n)$ . Then Condition SM(iii) holds if (1) the regressors  $f_i$  are Gaussian as in Lemma 1 or (2) the regressors  $f_i$  are arbitrary i.i.d. vectors with bounded entries as in Lemma 2.*

The first result describes the properties of the IV estimator with the optimal IV constructed using Lasso or Post-Lasso in the setting of the standard model. The result also provides a consistent estimator for the asymptotic variance of this estimator under heteroscedasticity.

**Theorem 3** (Inference with Optimal IV Estimated by Lasso or Post-Lasso). *Suppose that data  $(y_i, x_i, d_i)$  are i.n.i.d. and obey the linear IV model described in Section 2. Suppose also that Conditions AS, RF, SM, (2.7) and (3.13) hold. To construct the estimate of the optimal instrument, suppose that Condition RE holds in the case of using Lasso or that Condition SE and (3.14) hold in the case of using Post-Lasso. Then the IV estimator  $\hat{\alpha}$ , based on either Lasso or Post-Lasso estimates of the optimal instrument, is root- $n$  consistent and asymptotically normal:*

$$(Q^{-1}\Omega Q^{-1})^{-1/2}\sqrt{n}(\hat{\alpha} - \alpha_0) \rightarrow_d N(0, I),$$

for  $\Omega := \bar{\mathbb{E}}[\epsilon_i^2 D(x_i) D(x_i)']$  and  $Q := \bar{\mathbb{E}}[D(x_i) D(x_i)']$ . Moreover, the result above continues to hold with  $\Omega$  replaced by  $\hat{\Omega} := \mathbb{E}_n[\hat{\epsilon}_i^2 \hat{D}(x_i) \hat{D}(x_i)']$  for  $\hat{\epsilon}_i = y_i - d_i' \hat{\alpha}$ , and  $Q$  replaced by  $\hat{Q} := \mathbb{E}_n[\hat{D}(x_i) \hat{D}(x_i)']$ . In the case that the structural error  $\epsilon_i$  is homoscedastic conditional on  $x_i$ , that is,  $E[\epsilon_i^2 | x_i] = \sigma^2$  a.s. for all  $i = 1, \dots, n$ , the IV estimator  $\hat{\alpha}$  based on either Lasso or Post-Lasso estimates of the optimal instrument is root- $n$  consistent, asymptotically normal, and achieves the efficiency bound:  $(\Lambda^*)^{-1/2} \sqrt{n}(\hat{\alpha} - \alpha_0) \rightarrow_d N(0, I)$  where  $\Lambda^* := \sigma^2 Q^{-1}$ . The result above continues to hold with  $\Lambda^*$  replaced by  $\hat{\Lambda}^* := \hat{\sigma}^2 \hat{Q}^{-1}$ , where  $\hat{Q} := \mathbb{E}_n[\hat{D}(x_i) \hat{D}(x_i)']$  and  $\hat{\sigma}^2 := \mathbb{E}_n[(y_i - d_i' \hat{\alpha})^2]$ .

In the setting with homoscedastic structural errors the estimator achieves the efficiency bound asymptotically. In the case of heteroscedastic structural errors, the estimator does not achieve the efficiency bound, but we can expect it to be close to achieving the bound if heteroscedasticity is mild.

The final result of this section extends the previous result to any IV-estimator with a generic sparse estimator of the optimal instruments.

**Theorem 4** (Inference with IV Constructed by a Generic Sparsity-Based Procedure). *Suppose that conditions AS and SM hold, and suppose that the fitted values of the optimal instrument,  $\hat{D}_{il} = f_i' \hat{\beta}_l$ , are constructed using any estimator  $\hat{\beta}_l$  such that*

$$\max_{1 \leq l \leq k_e} \|\hat{D}_{il} - D_{il}\|_{2,n} \lesssim_P \sqrt{\frac{s \log(p \vee n)}{n}} \quad \text{and} \quad \max_{1 \leq l \leq k_e} \|\hat{\beta}_l - \beta_{l0}\|_1 \lesssim_P \sqrt{\frac{s^2 \log(p \vee n)}{n}}. \quad (4.15)$$

*Then the conclusions reached in Theorem 3 continue to apply.*

This result shows that the previous two theorems apply for any first-stage estimator that attains near-oracle performance given in (4.15). Examples of other sparse estimators covered by this theorem are Dantzig and Gauss-Dantzig (Candes and Tao, 2007),  $\sqrt{\text{Lasso}}$  and post- $\sqrt{\text{Lasso}}$  (Belloni, Chernozhukov, and Wang, 2011a and 2011b), thresholded Lasso and Post-thresholded Lasso (Belloni and Chernozhukov, 2012), group Lasso and Post-group Lasso (Huang, Horowitz, and Wei, 2010; and Lounici, Pontil, Tsybakov, and van de Geer, 2010), adaptive versions of the above (Huang, Horowitz, and Wei, 2010), and boosting (Bühlmann, 2006). Verification of the near-oracle performance (4.15) can be done on a case by case basis using the best conditions in the literature.<sup>10</sup> Our results extend to Lasso-type estimators under alternative forms of regularity conditions that fall outside the framework of Conditions RE and Conditions RF; all that is required is the near-oracle performance of the kind (4.15).

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<sup>10</sup>Post- $\ell_1$ -penalized procedures have only been analyzed for the case of Lasso and  $\sqrt{\text{Lasso}}$ ; see Belloni and Chernozhukov (2012) and Belloni, Chernozhukov, and Wang (2011a). We expect that similar results carry over to other procedures listed above.

**4.2. Inference when instruments are weak.** When instruments are weak individually, Lasso may end up selecting no instruments or may produce unreliable estimates of the optimal instruments. To cover this case, we propose a method for inference based on inverting pointwise tests performed using a sup-score statistic defined below. The procedure is similar in spirit to Anderson and Rubin (1949) and Staiger and Stock (1997) but uses a different statistics that is better suited to cases with very many instruments. In order to describe the approach, we rewrite the main structural equation as:

$$y_i = d_{ei}'\alpha_1 + w_i'\alpha_2 + \epsilon_i, \quad \mathbb{E}[\epsilon_i|x_i] = 0, \quad (4.16)$$

where  $y_i$  is the response variable,  $d_{ei}$  is a vector of endogenous variables,  $w_i$  is a  $k_w$ -vector of control variables,  $x_i = (z_i', w_i')'$  is a vector of elementary instrumental variables, and  $\epsilon_i$  is a disturbance such that  $\epsilon_1, \dots, \epsilon_n$  are i.n.i.d. conditional on  $X = [x_1', \dots, x_n']$ . We partition  $d_i = (d_{ei}', w_i')'$ . The parameter of interest is  $\alpha_1 \in \mathcal{A}_1 \subset \mathbb{R}^{k_e}$ . We use  $f_i = P(x_i)$ , a vector which includes  $w_i$ , as technical instruments. In this subsection, we treat  $X$  as fixed; i.e. we condition on  $X$ .

We would like to use a high-dimensional vector  $f_i$  of technical instruments for inference on  $\alpha_1$  that is robust to weak identification. In order to formulate a practical sup-score statistic, it is useful to partial-out the effect of  $w_i$  on the key variables. For an  $n$ -vector  $\{u_i, i = 1, \dots, n\}$ , define  $\tilde{u}_i = u_i - w_i'\mathbb{E}_n[w_i w_i']^{-1}\mathbb{E}_n[w_i u_i]$ , i.e. the residuals left after regressing this vector on  $\{w_i, i = 1, \dots, n\}$ . Hence  $\tilde{y}_i$ ,  $\tilde{d}_{ei}$ , and  $\tilde{f}_{ij}$  are residuals obtained by partialling out controls  $w_i$ . Also, let

$$\tilde{f}_i = (\tilde{f}_{i1}, \dots, \tilde{f}_{ip})'. \quad (4.17)$$

In this formulation, we omit elements of  $w_i$  from  $\tilde{f}_{ij}$  since they are eliminated by partialling out. We then normalize these technical instruments so that

$$\mathbb{E}_n[\tilde{f}_{ij}^2] = 1, \quad j = 1, \dots, p. \quad (4.18)$$

The sup-score statistic for testing the hypothesis  $\alpha_1 = a$  takes the form

$$\Lambda_a = \max_{1 \leq j \leq p} |n\mathbb{E}_n[(\tilde{y}_i - \tilde{d}_{ei}'a)\tilde{f}_{ij}]| / \sqrt{\mathbb{E}_n[(\tilde{y}_i - \tilde{d}_{ei}'a)^2 \tilde{f}_{ij}^2]}. \quad (4.19)$$

As before, we apply self-normalized moderate deviation theory for self-normalized sums to obtain

$$\mathbb{P}(\Lambda_{\alpha_1} \leq c\sqrt{n}\Phi^{-1}(1 - \gamma/2p)) \geq 1 - \gamma + o(1).$$

Therefore, we can employ  $\Lambda(1 - \gamma) := c\sqrt{n}\Phi^{-1}(1 - \gamma/2p)$  for  $c > 1$  as a critical value for testing  $\alpha_1 = a$  using  $\Lambda_a$  as the test-statistic. The asymptotic  $(1 - \gamma)$  - confidence region for  $\alpha_1$  is then given by  $\mathcal{C} := \{a \in \mathcal{A}_1 : \Lambda_a \leq \Lambda(1 - \gamma)\}$ .

The construction of confidence regions above can be given the following *Inverse Lasso* interpretation. Let

$$\hat{\beta}_a \in \arg \min_{\beta \in \mathbb{R}^p} \mathbb{E}_n[(\tilde{y}_i - \tilde{d}'_{ei}a) - \tilde{f}'_{ij}\beta]^2 + \frac{\lambda}{n} \sum_{j=1}^p \gamma_{aj} |\beta_j|, \quad \gamma_{aj} = \sqrt{\mathbb{E}_n[(\tilde{y}_i - \tilde{d}'_{ei}a)^2 \tilde{f}_{ij}^2]}.$$

If  $\lambda = 2\Lambda(1 - \gamma)$ , then  $\mathcal{C}$  is equivalent to the region  $\{a \in \mathbb{R}^{k_e} : \hat{\beta}_a = 0\}$ . In words, this confidence region collects all potential values of the structural parameter where the Lasso regression of the potential structural disturbance on the instruments yields zero coefficients on the instruments. This idea is akin to the Inverse Quantile Regression and Inverse Least Squares ideas in Chernozhukov and Hansen (2008a, 2008b).

Below, we state the main regularity condition for the validity of inference using the sup-score statistic as well as the formal inference result.

**Condition SM2.** Suppose that for each  $n$  the linear model (4.16) holds with  $\alpha_1 \in \mathcal{A}_1 \subset \mathbb{R}^{k_e}$  such that  $\epsilon_1, \dots, \epsilon_n$  are i.n.i.d.,  $X$  is fixed, and  $\tilde{f}_1, \dots, \tilde{f}_n$  are  $p$ -vectors of technical instruments defined in (4.17) and (4.18). Suppose that (i) the dimension of  $w_i$  is  $k_w$  and  $\|w_i\|_2 \leq \zeta_w$  such that  $\sqrt{k_w}\zeta_w/\sqrt{n} \rightarrow 0$ , (ii) the eigenvalues of  $\mathbb{E}_n[w_i w_i']$  are bounded away from zero and eigenvalues of  $\bar{\mathbb{E}}[\epsilon_i^2 w_i w_i']$  are bounded away from above, uniformly in  $n$ , (iii)  $\max_{1 \leq j \leq p} \bar{\mathbb{E}}[|\epsilon_i|^3 |\tilde{f}_{ij}|^3]^{1/3} / \bar{\mathbb{E}}[\epsilon_i^2 \tilde{f}_{ij}^2]^{1/2} \leq K_n$ , and (iv)  $K_n^2 \log(p \vee n) = o(n^{1/3})$ .

**Theorem 5** (Valid Inference based on the Sup-Score Statistic). Let  $\gamma \in (0, 1)$  be fixed or, more generally, such that  $\log(1/\gamma) \lesssim \log(p \vee n)$ . Under Condition SM2, (1) in large samples, the constructed confidence set  $\mathcal{C}$  contains the true value  $\alpha_1$  with at least the prescribed probability, namely  $\mathbb{P}(\alpha_1 \in \mathcal{C}) \geq 1 - \gamma - o(1)$ . (2) Moreover, the confidence set  $\mathcal{C}$  necessarily excludes a sequence of parameter value  $a$ , namely  $\mathbb{P}(a \in \mathcal{C}) \rightarrow 0$ , if

$$\max_{1 \leq j \leq p} \frac{\sqrt{n/\log(p/\gamma)} \|\mathbb{E}_n[(a - \alpha_1)' \tilde{d}_{ei} \tilde{f}_{ij}]\|}{c \sqrt{\mathbb{E}_n[\epsilon_i^2 \tilde{f}_{ij}^2]} + \sqrt{\mathbb{E}_n[\{(a - \alpha_1)' \tilde{d}_{ei}\}^2 \tilde{f}_{ij}^2]}} \rightarrow_{\mathbb{P}} \infty.$$

The theorem shows that the confidence region  $\mathcal{C}$  constructed above is valid in large samples and that the probability of including a false point  $a$  in  $\mathcal{C}$  tends to zero as long as  $a$  is sufficiently distant from  $\alpha_1$  and instruments are not too weak. In particular, if there is a strong instrument, the confidence regions will eventually exclude points  $a$  that are further than  $\sqrt{\log(p \vee n)/n}$  away from  $\alpha_1$ . Moreover, if there are instruments whose correlation with the endogenous variable is of greater order than  $\sqrt{\log(p \vee n)/n}$ , then the confidence regions will asymptotically be bounded.

## 5. FURTHER INFERENCE AND ESTIMATION RESULTS FOR THE IV MODEL

In this section we provide further estimation and inference results. We develop an overidentification test which compares the IV-Lasso based estimates to estimates obtained using a baseline

set of instruments. We also combine the IV selection using Lasso with a sample-splitting technique from the many instruments literature which allows us to relax the growth requirement on the number of relevant instruments.

**5.1. A Specification Test for Validity of Instrumental Variables.** Here we develop a Hausman-style specification test for the validity of the instrumental variables. Let  $A_i = A(x_i)$  be a baseline set of instruments, with  $\dim(A_i) \geq \dim(\alpha) = k_\alpha$  bounded. Let  $\tilde{\alpha}$  be the baseline instrumental variable estimator based on these instruments:

$$\tilde{\alpha} = (\mathbb{E}_n[d_i A_i'] \mathbb{E}_n[A_i A_i']^{-1} \mathbb{E}_n[A_i d_i'])^{-1} \mathbb{E}_n[d_i A_i'] \mathbb{E}_n[A_i A_i']^{-1} \mathbb{E}_n[A_i y_i].$$

If the instrumental variable exclusion restriction is valid, then the unscaled difference between this estimator and the IV estimator  $\hat{\alpha}$  proposed in the previous sections should be small. If the exclusion restriction is not valid, the difference between  $\tilde{\alpha}$  and  $\hat{\alpha}$  should be large. Therefore, we can reject the null hypothesis of instrument validity if the difference is large.

We formalize the test as follows. Suppose we care about  $R'\alpha$  for some  $k \times k_d$  matrix  $R$  of  $\text{rank}(R) = k$ . For instance, we might care only about the first  $k$  components of  $\alpha$ , in which case  $R = [I_k \ 0]$  is a  $k \times k_d$  matrix that selects the first  $k$  coefficients of  $\alpha$ . Define the estimand for  $\tilde{\alpha}$  as

$$\alpha = (\bar{\mathbb{E}}[d_i A_i'] \bar{\mathbb{E}}[A_i A_i']^{-1} \bar{\mathbb{E}}[A_i d_i'])^{-1} \bar{\mathbb{E}}[d_i A_i'] \bar{\mathbb{E}}[A_i A_i']^{-1} \bar{\mathbb{E}}[A_i y_i],$$

and define the estimand of  $\hat{\alpha}$  as

$$\alpha_a = \bar{\mathbb{E}}[D(x_i) D(x_i)']^{-1} \bar{\mathbb{E}}[D(x_i) y_i].$$

The null hypothesis  $H_0$  is  $R(\alpha - \alpha_a) = 0$  and the alternative  $H_a$  is  $R(\alpha - \alpha_a) \neq 0$ . We can form a test statistic

$$J = \sqrt{n}(\tilde{\alpha} - \hat{\alpha})' R' (R \hat{\Sigma} R')^{-1} \sqrt{n} R(\tilde{\alpha} - \hat{\alpha})$$

for a matrix  $\hat{\Sigma}$  defined below and reject  $H_0$  if  $J > c_\gamma$  where  $c_\gamma$  is the  $(1-\gamma)$ -quantile of chi-square random variable with  $k$  degrees of freedom. The justification for this test is provided by the following theorem which builds upon the previous results coupled with conventional results for the baseline instrumental variable estimator.<sup>11</sup>

**Theorem 6** (Specification Test). *(1) Suppose the conditions of Theorem 3 hold, that  $\bar{\mathbb{E}}[\|A_i\|_2^q]$  is bounded uniformly in  $n$  for  $q > 4$ , and the eigenvalues of*

$$\Sigma := \bar{\mathbb{E}}[\epsilon_i^2 (M A_i - Q^{-1} D(x_i))(M A_i - Q^{-1} D(x_i))']$$

*are bounded from above and below, uniformly in  $n$ , where*

$$M = (\bar{\mathbb{E}}[d_i A_i'] \bar{\mathbb{E}}[A_i A_i']^{-1} \bar{\mathbb{E}}[A_i d_i'])^{-1} \bar{\mathbb{E}}[d_i A_i'] \bar{\mathbb{E}}[A_i A_i']^{-1}.$$

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<sup>11</sup>The proof of this result is provided in a supplementary appendix.



Then  $\sqrt{n}\widehat{\Sigma}^{-1/2}(\tilde{\alpha} - \widehat{\alpha})' \rightarrow_d N(0, I)$  and  $J \rightarrow_d \chi^2(k)$ , where

$$\widehat{\Sigma} = \mathbb{E}_n[\widehat{\epsilon}_i^2(\widehat{M}^{-1}A_i - \widehat{Q}^{-1}\widehat{D}(x_i))(\widehat{M}^{-1}A_i - \widehat{Q}^{-1}\widehat{D}(x_i))'],$$

for  $\widehat{\epsilon}_i = y_i - d_i'\widehat{\alpha}$ ,  $\widehat{Q} = \mathbb{E}_n[\widehat{D}(x_i)\widehat{D}(x_i)']$ , and

$$\widehat{M} = (\mathbb{E}_n[d_i A_i'] \mathbb{E}_n[A_i A_i']^{-1} \mathbb{E}_n[A_i d_i'])^{-1} \mathbb{E}_n[d_i A_i'] \mathbb{E}_n[A_i A_i']^{-1}.$$

(2) Suppose the conditions of Theorem 3 hold with the exception that  $\mathbb{E}[A_i \epsilon_i] = 0$  for all  $i = 1, \dots, n$  and  $n$ , but  $\|\bar{\mathbb{E}}[D(x_i) \epsilon_i]\|_2$  is bounded away from zero. Then  $J \rightarrow_P \infty$ .

**5.2. Split-sample IV estimator.** The rate condition  $s^2 \log^2(p \vee n) = o(n)$  can be substantive and cannot be substantially weakened for the full-sample IV estimator considered above. However, we can replace this condition with the weaker condition that

$$s \log(p \vee n) = o(n)$$

by employing a sample splitting method from the many instruments literature (Angrist and Krueger, 1995). Specifically, we consider dividing the sample randomly into (approximately) equal parts  $a$  and  $b$ , with sizes  $n_a = \lceil n/2 \rceil$  and  $n_b = n - n_a$ . We use superscripts  $a$  and  $b$  for variables in the first and second subsample respectively. The index  $i$  will enumerate observations in both samples, with ranges for the index given by  $1 \leq i \leq n_a$  for sample  $a$  and  $1 \leq i \leq n_b$  for sample  $b$ . We can use each of the subsamples to fit the first stage via Lasso or Post-Lasso to obtain the first stage estimates  $\widehat{\beta}_l^k, k = a, b$ , and  $l = 1, \dots, k_e$ . Then setting  $\widehat{D}_{il}^a = f_i^{a'} \widehat{\beta}_l^a, 1 \leq i \leq n_a$ ,  $\widehat{D}_{il}^b = f_i^{b'} \widehat{\beta}_l^b, 1 \leq i \leq n_b$ ,  $\widehat{D}_i^k = (\widehat{D}_{i1}^k, \dots, \widehat{D}_{ik_e}^k, w_i^{k'})', k = a, b$ , we form the IV estimates in the two subsamples:

$$\widehat{\alpha}_a = \mathbb{E}_{n_a}[\widehat{D}_i^a d_i^{a'}]^{-1} \mathbb{E}_{n_a}[\widehat{D}_i^a y_i^a] \quad \text{and} \quad \widehat{\alpha}_b = \mathbb{E}_{n_b}[\widehat{D}_i^b d_i^{b'}]^{-1} \mathbb{E}_{n_b}[\widehat{D}_i^b y_i^b].$$

Then we combine the estimates into one

$$\widehat{\alpha}_{ab} = (n_a \mathbb{E}_{n_a}[\widehat{D}_i^a \widehat{D}_i^{a'}] + n_b \mathbb{E}_{n_b}[\widehat{D}_i^b \widehat{D}_i^{b'}])^{-1} (n_a \mathbb{E}_{n_a}[\widehat{D}_i^a \widehat{D}_i^{a'}] \widehat{\alpha}_a + n_b \mathbb{E}_{n_b}[\widehat{D}_i^b \widehat{D}_i^{b'}] \widehat{\alpha}_b). \quad (5.20)$$

The following result shows that the split-sample IV estimator  $\widehat{\alpha}_{ab}$  has the same large sample properties as the estimator  $\widehat{\alpha}$  of the previous section but requires a weaker growth condition.

**Theorem 7** (Inference with a Split-Sample IV Based on Lasso or Post-Lasso). *Suppose that data  $(y_i, x_i, d_i)$  are i.n.i.d. and obey the linear IV model described in Section 2. Suppose also that Conditions AS, RF, SM, (2.7), (3.13) and (3.14) hold, except that instead of growth condition  $s^2 \log^2(p \vee n) = o(n)$  we now have a weaker growth condition  $s \log(p \vee n) = o(n)$ . Suppose also that Condition SE hold for  $M^k = \mathbb{E}_{n_k}[f_i^k f_i^{k'}]$  for  $k = a, b$ . Let  $\widehat{D}_{il}^k = f_i^{k'} \widehat{\beta}_l^{k^c}$  where  $\widehat{\beta}_l^{k^c}$  is the Lasso or Post-Lasso estimator applied to the subsample  $\{(d_{li}^{k^c}, f_i^{k^c}) : 1 \leq i \leq n_{k^c}\}$  for  $k = a, b$ , and  $k^c = \{a, b\} \setminus k$ . Then the split-sample IV estimator based on equation (5.20) is  $\sqrt{n}$ -consistent and asymptotically normal, as  $n \rightarrow \infty$*

$$(Q^{-1} \Omega Q^{-1})^{-1/2} \sqrt{n}(\widehat{\alpha}_{ab} - \alpha_0) \rightarrow_d N(0, I),$$

for  $\Omega := \bar{\mathbb{E}}[\epsilon_i^2 D(x_i) D(x_i)']$  and  $Q := \bar{\mathbb{E}}[D(x_i) D(x_i)']$ . Moreover, the result above continues to hold with  $\Omega$  replaced by  $\hat{\Omega} := \mathbb{E}_n[\hat{\epsilon}_i^2 \hat{D}(x_i) \hat{D}(x_i)']$  for  $\hat{\epsilon}_i = y_i - d_i' \hat{\alpha}_{ab}$ , and  $Q$  replaced by  $\hat{Q} := \mathbb{E}_n[\hat{D}(x_i) \hat{D}(x_i)']$ .

## 6. SIMULATION EXPERIMENT

The previous sections' results suggest that using Lasso for fitting first-stage regressions should result in IV estimators with good estimation and inference properties. In this section, we provide simulation evidence regarding these properties in a situation where there are many possible instruments. We also compare the performance of the developed Lasso-based estimators to many-instrument robust estimators that are available in the literature.

Our simulations are based on a simple instrumental variables model data generating process (DGP):

$$\begin{aligned} y_i &= \beta d_i + e_i \\ d_i &= z_i' \Pi + v_i \end{aligned} \quad (e_i, v_i) \sim N \left( 0, \begin{pmatrix} \sigma_e^2 & \sigma_{ev} \\ \sigma_{ev} & \sigma_v^2 \end{pmatrix} \right) \text{ i.i.d.}$$

where  $\beta = 1$  is the parameter of interest, and  $z_i = (z_{i1}, z_{i2}, \dots, z_{i100})' \sim N(0, \Sigma_Z)$  is a 100 x 1 vector with  $E[z_{ih}^2] = \sigma_z^2$  and  $\text{Corr}(z_{ih}, z_{ij}) = .5^{|j-h|}$ . In all simulations, we set  $\sigma_e^2 = 1$  and  $\sigma_z^2 = 1$ . We also set  $\text{Corr}(e, v) = 0.6$ .

For the other parameters, we consider various settings. We provide results for sample sizes,  $n$ , of 100 and 250. We set  $\sigma_v^2$  so that the unconditional variance of the endogenous variable equals one; i.e.  $\sigma_v^2 = 1 - \Pi' \Sigma_Z \Pi$ . We use three different settings for the pattern of the first-stage coefficients,  $\Pi$ . In the first, we set  $\Pi = C \tilde{\Pi} = C(1, .7, .7^2, \dots, .7^{98}, .7^{99})'$ ; we term this the “exponential” design. In the second and third case, we set  $\Pi = C \tilde{\Pi} = C(\iota_s, 0_{n-s})'$  where  $\iota_s$  is a  $1 \times s$  vector of ones and  $0_{n-s}$  is a  $1 \times n - s$  vector of zeros. We term this the “cut-off” design and consider two different values of  $s$ ,  $s = 5$  and  $s = 50$ . In the exponential design, the model is not literally sparse although the majority of explanatory power is contained in the first few instruments. While the model is exactly sparse in the cut-off design, we expect Lasso to perform poorly with  $s = 50$  since treating  $\frac{s^2 \log^2 p}{n}$  as vanishingly small seems like a poor approximation given the sample sizes considered. We consider different values of the constant  $C$  that are chosen to generate target values for the concentration parameter,  $\mu^2 = \frac{n \Pi' \Sigma_Z \Pi}{\sigma_v^2}$ , which plays a key role in the behavior of IV estimators; see, e.g. Stock, Wright, and Yogo (2002) or Hansen, Hausman, and Newey (2008).<sup>12</sup> Specifically, we choose  $C$  to solve  $\mu^2 = \frac{n C^2 \tilde{\Pi} \Sigma_Z \tilde{\Pi}}{1 - C^2 \tilde{\Pi} \Sigma_Z \tilde{\Pi}}$  for  $\mu^2 = 30$  and for

<sup>12</sup>The concentration parameter is closely related to the first-stage Wald statistic and first-stage F-statistic for testing that the coefficients on the instruments are equal to 0. Under homoscedasticity, the first-stage Wald statistic is  $W = \hat{\Pi}'(Z'Z)\hat{\Pi}/\hat{\sigma}_v^2$  and the first-stage F-statistic is  $W/\text{dim}(Z)$ .

$\mu^2 = 180$ . These values of the concentration parameter were chosen by using estimated values from the empirical example reported below as a benchmark.<sup>13</sup>

For each setting of the simulation parameter values, we report results from seven different procedures. A simple possibility when presented with many instrumental variables (with  $p < n$ ) is to just estimate the model using 2SLS and all of the available instruments. It is well-known that this will result in poor-finite sample properties unless there are many more observations than instruments; see, for example, Bekker (1994). The estimator proposed in Fuller (1977) (FULL) is robust to many instruments (with  $p < n$ ) as long as the presence of many instruments is accounted for when constructing standard errors for the estimators; see Hansen, Hausman, and Newey (2008) for example.<sup>14</sup> We report results for these estimators in rows labeled 2SLS(100) and FULL(100) respectively.<sup>15</sup> For our variable selection procedures, we use Lasso to select among the instruments using the refined data-dependent penalty loadings given in (A.21) described in Appendix A and consider two post-model selection estimation procedures. The first, Post-Lasso, runs 2SLS using the instruments selected by Lasso; and the second, Post-Lasso-F, runs FULL using the instruments selected by Lasso. In cases where no instruments are selected by Lasso, we use the point-estimate obtained by running 2SLS with the single instrument with the highest within sample correlation to the endogenous variable as the point estimate for Post-Lasso and Post-Lasso-F. In these cases, we use the sup-Score test for performing inference.<sup>16</sup> We report inference results based on the weak-identification robust sup-score testing procedure in rows labeled “sup-Score”.

The other two procedure “Post-Lasso (Ridge)” and “Post-Lasso-F (Ridge)” use a combination of Ridge regression, Lasso, and sample-splitting. For these procedures, we randomly split the sample into two equal-sized parts. Call these sub-samples “sample A” and “sample B.” We then use leave-one-out cross-validation with only the data in sample A to select a ridge penalty parameter and then estimate a set of ridge coefficients using this penalty and the data from sample A. We then use the data from sample B with these coefficients estimated using only data from sample A to form first-stage fitted values for sample B. Then, we take the full-set of instruments augmented with the estimated fitted value just described and perform Lasso variable

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<sup>13</sup>In the empirical example, first-stage Wald statistics based on the selected instruments range from between 44 and 243. In the cases with constant coefficients, our concentration parameter choices correspond naturally to “infeasible F-statistics” defined as  $\mu^2/s$  of 6 and 36 with  $s = 5$  and .6 and 3.6 with  $s = 50$ . In an online appendix, we provide additional simulation results. The results reported in the current section are sufficient to capture the key patterns.

<sup>14</sup>FULL requires a user-specified parameter. We set this parameter equal to one which produces a higher-order unbiased estimator. See Hahn, Hausman, and Kuersteiner (2004) for additional discussion. LIML is another commonly proposed estimator which is robust to many instruments. In our designs, its performance was generally similar to that of FULL, and we report only FULL for brevity.

<sup>15</sup>With  $n = 100$ , estimates are based on a randomly selected 99 instruments.

<sup>16</sup>Inference based on the asymptotic approximation when Lasso selects instruments and based on the sup-Score test when Lasso fails to select instruments is our preferred procedure.

selection using only the data from sample B. We use the selected variables to run either 2SLS or Fuller in sample B to obtain estimates of  $\beta$  (and associated standard errors), say  $\hat{\beta}_{B,2SLS}$  ( $s_{B,2SLS}$ ) and  $\hat{\beta}_{B,Fuller}$  ( $s_{B,Fuller}$ ). We then repeat this exercise switching sample A and B to obtain estimates of  $\beta$  (and associated standard errors) from sample A, say  $\hat{\beta}_{A,2SLS}$  ( $s_{A,2SLS}$ ) and  $\hat{\beta}_{A,Fuller}$  ( $s_{A,Fuller}$ ). Post-Lasso (Ridge) is then  $w_{A,2SLS}\hat{\beta}_{A,2SLS} + (1 - w_{A,2SLS})\hat{\beta}_{B,2SLS}$  for  $w_{A,2SLS} = \frac{s_{B,2SLS}^2}{s_{A,2SLS}^2 + s_{B,2SLS}^2}$ , and Post-Lasso-F (Ridge) is defined similarly. If instruments are selected in one subsample but not in the other, we put weight one on the estimator from the subsample where instruments were selected. If no instruments are selected in either subsample, we use the single-instrument with the highest correlation to obtain the point estimate and use the sup-score test for performing inference.

For each estimator, we report median bias (Med. Bias), median absolute deviation (MAD), and rejection frequencies for 5% level tests (rp(.05)). For computing rejection frequencies, we estimate conventional, homoscedastic 2SLS standard errors for 2SLS(100) and Post-Lasso and the many instrument robust standard errors of Hansen, Hausman, and Newey (2008) which rely on homoscedasticity for FULL(100) and Post-Lasso-F. We report the number of cases in which Lasso selected no instruments in the column labeled N(0).

We summarize the simulation results in Table 1. It is apparent that the Lasso procedures are dominant when  $n = 100$ . In this case, the Lasso-based procedures outperform 2SLS(100) and FULL(100) on all dimensions considered. When the concentration parameter is 30 or  $s = 50$ , the instruments are relatively weak, and Lasso accordingly selects no instruments in many cases. In these cases, inference switches to the robust sup-score procedure which controls size. With a concentration parameter of 180, the instruments are relatively more informative and sparsity provides a good approximation in the exponential design and  $s = 5$  cut-off design. In these cases, Lasso selects instruments in the majority of replications and the procedure has good risk and inference properties relative to the other procedures considered. In the  $n = 100$  case, the simple Lasso procedures also clearly dominate Lasso augmented with Ridge as this procedure often results in no instruments being selected and relatively low power; see Figure 1. We also see that the sup-score procedure controls size across the designs considered.

In the  $n = 250$  case, the conventional many-instrument asymptotic sequence which has  $p$  proportional to  $n$  but  $p/n < 1$  provides a reasonable approximation to the DGP, and one would expect FULL to perform well. In this case, 2SLS(100) is clearly dominated by the other procedures. However, there is no obvious ranking between FULL(100) and the Lasso-based procedures. With  $s = 50$ , sparsity is a poor approximation in that there is signal in the combination of the 50 relevant instruments but no small set of instruments has much explanatory power. In this setting, FULL(100) has lower estimation risk than the Lasso procedure which is not effectively able to capture the diffuse signal though both inference procedures have size close to the prescribed level. Lasso augmented with the Ridge fit also does relatively well in

this setting, being roughly on par with FULL(100). In the exponential and cut-off with  $s = 5$  designs, sparsity is a much better approximation. In these cases, the simple Lasso-based estimators have smaller risk than FULL(100) or Lasso with Ridge and produce tests that have size close to the nominal 5% level. Finally, we see that the sup-score procedure continues to control size with  $n = 250$ .

Given that the sup-score procedure uniformly controls size across the designs considered but is actually substantially undersized, it is worth presenting additional results regarding power. We plot size-adjusted power curves for the sup-score test, Post-Lasso-F, Post-Lasso-F (Ridge), and FULL(100) across the different designs in the  $\mu^2 = 180$  cases in Figure 1. We focus on  $\mu^2 = 180$  since we expect it is when identification is relatively strong that differences in power curves will be most pronounced. From these curves, it is apparent that the robustness of the sup-score test comes with a substantial loss of power in cases where identification is strong. Exploring other procedures that are robust to weak identification, allow for  $p \gg n$ , and do not suffer from such power losses may be interesting for future research.

**6.1. Conclusions from Simulation Experiments.** The evidence from the simulations is supportive of the derived theory and favorable to Lasso-based IV methods. The Lasso-IV estimators clearly dominate on all metrics considered when  $p = n$  and  $s \ll n$ . The Lasso-based IV estimators generally have relatively small median bias and estimator risk and do well in terms of testing properties, though they do not dominate FULL in these dimensions across all designs with  $p < n$ . The simulation results verify that FULL becomes more appealing as the sparsity assumption breaks down. This breakdown of sparsity is likely in situations with weak instruments, be they many or few, where none of the first-stage coefficients are well-separated from zero relative to sampling variation. Overall, the simulation results show that simple Lasso-based procedures can usefully complement other many-instrument methods.

## 7. THE IMPACT OF EMINENT DOMAIN ON ECONOMIC OUTCOMES

As an example of the potential application of Lasso to select instruments, we consider IV estimation of the effects of federal appellate court decisions regarding eminent domain on a variety of economic outcomes.<sup>17</sup> To try to uncover the relationship between takings law and economic outcomes, we estimate structural models of the form

$$y_{ct} = \alpha_c + \alpha_t + \gamma_c t + \beta \text{ Takings Law}_{ct} + W'_{ct} \delta + \epsilon_{ct}$$

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<sup>17</sup>See Chen and Yeh (2010) for a detailed discussion of the economics of takings law (or eminent domain), relevant institutional features of the legal system, and a careful discussion of endogeneity concerns and the instrumental variables strategy in this context.

where  $y_{ct}$  is an economic outcome for circuit  $c$  at time  $t$ ,  $Takings\ Law_{ct}$  represents the number of pro-plaintiff appellate takings decisions in circuit  $c$  and year  $t$ ;  $W_{ct}$  are judicial pool characteristics,<sup>18</sup> a dummy for whether there were no cases in that circuit-year, and the number of takings appellate decisions; and  $\alpha_c$ ,  $\alpha_t$ , and  $\gamma_{ct}$  are respectively circuit-specific effects, time-specific effects, and circuit-specific time trends. An appellate court decision is coded as pro-plaintiff if the court ruled that a taking was unlawful, thus overturning the government’s seizure of the property in favor of the private owner. We construe pro-plaintiff decisions to indicate a regime that is more protective of individual property rights. The parameter of interest,  $\beta$ , thus represents the effect of an additional decision upholding individual property rights on an economic outcome.

We provide results using four different economic outcomes: the log of three home-price-indices and  $\log(\text{GDP})$ . The three different home-price-indices we consider are the quarterly, weighted, repeat-sales FHFA/OFHEO house price index that tracks single-family house prices at the state level for metro (FHFA) and non-metro (Non-Metro) areas and the Case-Shiller home price index (Case-Shiller) by month for 20 metropolitan areas based on repeat-sales residential housing prices. We also use state level GDP from the Bureau of Economic Analysis to form  $\log(\text{GDP})$ . For simplicity and since all of the controls, instruments, and the endogenous variable vary only at the circuit-year level, we use the within-circuit-year average of each of these variables as the dependent variables in our models. Due to the different coverage and time series lengths available for each of these series, the sample sizes and sets of available controls differ somewhat across the outcomes. These differences lead to different first-stages across the outcomes as well. The total sample sizes are 312 for FHFA and GDP which have identical first-stages. For Non-Metro and Case-Shiller, the sample sizes are 110 and 183 respectively.

The analysis of the effects of takings law is complicated by the possible endogeneity between governmental takings and takings law decisions and economic variables. To address the potential endogeneity of takings law, we employ an instrumental variables strategy based on the identification argument of Chen and Sethi (2010) and Chen and Yeh (2010) that relies on the random assignment of judges to federal appellate panels. Since judges are randomly assigned to three judge panels to decide appellate cases, the exact identity of the judges and, more importantly, their demographics are randomly assigned conditional on the distribution of characteristics of federal circuit court judges in a given circuit-year. Thus, once the distribution of characteristics is controlled for, the realized characteristics of the randomly assigned three judge panel should be unrelated to other factors besides judicial decisions that may be related to economic outcomes.

There are many potential characteristics of three judge panels that may be used as instruments. While the basic identification argument suggests any set of characteristics of the three

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<sup>18</sup>The judicial pool characteristics are the probability of a panel being assigned with the characteristics used to construct the instruments. There are 30, 33, 32, and 30 controls available for FHFA house prices, non-metro house prices, Case-Shiller house prices, and GDP respectively.

judge panel will be uncorrelated with the structural unobservable, there will clearly be some instruments which are more worthwhile than others in obtaining precise second-stage estimates. For simplicity, we consider only the following demographics: gender, race, religion, political affiliation, whether the judge's bachelor was obtained in-state, whether the bachelor is from a public university, whether the JD was obtained from a public university, and whether the judge was elevated from a district court along with various interactions. In total, we have 138, 143, 147, and 138 potential instruments for FHFA prices, non-metro prices, Case-Shiller, and GDP respectively that we select among using Lasso.<sup>19</sup>

Table 3 contains estimation results for  $\beta$ . We report OLS estimates and results based on three different sets of instruments. The first set of instruments, used in the rows labeled 2SLS, are the instruments adopted in Chen and Yeh (2010).<sup>20</sup> We consider this the baseline. The second set of instruments are those selected through Lasso using the refined data-driven penalty.<sup>21</sup> The number of instruments selected by Lasso is reported in the row "S". We use the Post-Lasso 2SLS estimator and report these results in the rows labeled "Post-Lasso". The third set of instruments is simply the union of the first two instrument sets. Results for this set of instruments are in the rows labeled "Post-Lasso+". In this case, "S" is the total number of instruments used. In all cases, we use heteroscedasticity consistent standard error estimators. Finally, we report the value of the test statistic discussed in Section 4.3.1 comparing estimates using the first and second sets of instruments in the row labeled "Spec. Test".

The most interesting results from the standpoint of the present paper are found by comparing first-stage Wald-statistics and estimated standard errors across the instrument sets. The Lasso instruments are clearly much better first-stage predictors as measured by the first-stage Wald-statistic compared to the Chen and Yeh (2010) benchmark. Given the degrees of freedom, this increase obviously corresponds to Lasso-based IV providing a stronger first-stage relationship for FHFA prices, GDP, and the Case-Shiller prices. In the non-metro case, the p-value from the Wald test with the baseline instruments of Chen and Yeh (2010) is larger than that of the Lasso-selected instruments. This improved first-stage prediction is associated with the resulting

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<sup>19</sup>Given the sample sizes and numbers of variables, estimators using all the instruments without shrinkage are only defined in the GDP and FHFA data. For these outcomes, the Fuller (1977) point estimate (standard error) is -.0020 (3.123) for FHFA and .0120 (.1758) for GDP.

<sup>20</sup>Chen and Yeh (2010) used two variables motivated on intuitive grounds, whether a panel was assigned an appointee who did not report a religious affiliation and whether a panel was assigned an appointee who earned their first law degree from a public university, as instruments.

<sup>21</sup>Lasso selects the number of panels with at least one appointee whose law degree is from a public university (Public) cubed for GDP and FHFA. In the Case-Shiller data, Lasso selects Public and Public squared. For non-metro prices, Lasso selects Public interacted with the number of panels with at least one member who reports belonging to a mainline protestant religion, Public interacted with the number of panels with at least one appointee whose BA was obtained in-state (In-State), In-State interacted with the number of panels with at least one non-white appointee, and the interaction of the number of panels with at least one Democrat appointee with the number of panels with at least one Jewish appointee.

2SLS estimator having smaller estimated standard errors than the benchmark case for non-metro prices, Case-Shiller prices, and GDP. The reduction in standard errors is sizable for both non-metro and Case-Shiller. The standard error estimate is somewhat larger in the FHFA case despite the improvement in first-stage prediction. Given that the Post-Lasso first-stage produces a larger first-stage Wald-statistic while choosing fewer instruments than the benchmark suggests that we might prefer the Post-Lasso results in any case. We also see that the test statistics for testing the difference between the estimate using the Chen and Yeh (2010) instruments and the Post-Lasso estimate is equal to zero are uniformly small. Given the small differences between estimates using the first two sets of instruments, it is unsurprising that the results using the union of the two instrument sets are similar to those already discussed.

The results are also economically interesting. The point estimates for the effect of an additional pro-plaintiff decision, a decision in favor of individual property holders, are positive, suggesting these decisions are associated with increases in property prices and GDP. These point estimates are all small, and it is hard to draw any conclusion about the likely effect on GDP or the FHFA index given their estimated standard errors. On the other hand, confidence intervals for non-metro and Case-Shiller constructed at usual confidence levels exclude zero. Overall, the results do suggest that the causal effect of decisions reinforcing individual property rights is an increase in the value of holding property, at least in the short term. The results are also consistent with the developed asymptotic theory in that the 2SLS point-estimates based on the benchmark instruments are similar to the estimates based on the Lasso-selected instruments while Lasso produces a stronger first-stage relationship and the Post-Lasso estimates are more precise in three of the four cases. The example suggests that there is the potential for Lasso to be fruitfully employed to choose instruments in economic applications.

#### APPENDIX A. IMPLEMENTATION ALGORITHMS

It is useful to organize the precise implementation details into the following algorithm. We establish the asymptotic validity of this algorithm in the subsequent sections. Feasible options for setting the penalty level and the loadings for  $j = 1, \dots, p$ , and  $l = 1, \dots, k_e$  are

$$\begin{aligned} \text{initial} \quad \hat{\gamma}_{lj} &= \sqrt{\mathbb{E}_n[f_{ij}^2(d_{il} - \bar{d}_l)^2]}, & \lambda &= 2c\sqrt{n}\Phi^{-1}(1 - \gamma/(2k_ep)), \\ \text{refined} \quad \hat{\gamma}_{lj} &= \sqrt{\mathbb{E}_n[f_{ij}^2\hat{v}_{il}^2]}, & \lambda &= 2c\sqrt{n}\Phi^{-1}(1 - \gamma/(2k_ep)), \end{aligned} \tag{A.21}$$

where  $c > 1$  is a constant,  $\gamma \in (0, 1)$ ,  $\bar{d}_l := \mathbb{E}_n[d_{il}]$  and  $\hat{v}_{il}$  is an estimate of  $v_{il}$ . Let  $K \geq 1$  denote a bounded number of iterations. We used  $c = 1.1$ ,  $\gamma = 0.1/\log(p \vee n)$ , and  $K = 15$  in the simulations. In what follows Lasso/Post-Lasso estimator indicates that the practitioner can apply either the Lasso or Post-Lasso estimator. Our preferred approach uses Post-Lasso at every stage.



**Algorithm A.1** (Lasso/Post-Lasso Estimators). (1) For each  $l = 1, \dots, k_e$ , specify penalty loadings according to the initial option in (A.21). Use these penalty loadings in computing the Lasso/Post-Lasso estimator  $\hat{\beta}_l$  via equations (2.4) or (2.8). Then compute residuals  $\hat{v}_{il} = d_{li} - f_i' \hat{\beta}_l$ ,  $i = 1, \dots, n$ . (2) For each  $l = 1, \dots, k_e$ , update the penalty loadings according to the refined option in (A.21) and update the Lasso/Post-Lasso estimator  $\hat{\beta}_l$ . Then compute a new set of residuals using the updated Lasso/Post-Lasso coefficients  $\hat{v}_{il} = d_{li} - f_i' \hat{\beta}_l$ ,  $i = 1, \dots, n$ . (3) Repeat the previous step  $K$  times.

If the Algorithm A.1 selected no instruments other than intercepts, or, more generally if  $\mathbb{E}_n[\hat{D}_{il} \hat{D}_{il}']$  is near-singular, proceed to Algorithm A.3; otherwise, we recommend the following algorithm.

**Algorithm A.2** (IV Inference Using Estimates of Optimal Instrument). Compute the estimates of the optimal instrument,  $\hat{D}_{il} = f_i' \hat{\beta}_l$ , for  $i = 1, \dots, n$  and each  $l = 1, \dots, k_e$ , where  $\hat{\beta}_l$  is computed by Algorithm A.1. Compute the IV estimator  $\hat{\alpha} = \mathbb{E}_n[\hat{D}_i d_i']^{-1} \mathbb{E}_n[\hat{D}_i y_i]$ . (2) Compute estimates of the asymptotic variance matrix  $\hat{Q}^{-1} \hat{\Omega} \hat{Q}^{-1}$  where  $\hat{\Omega} := \mathbb{E}_n[\hat{\epsilon}_i^2 \hat{D}_i \hat{D}_i']$  for  $\hat{\epsilon}_i = y_i - d_i' \hat{\alpha}$ , and  $\hat{Q} := \mathbb{E}_n[\hat{D}_i \hat{D}_i']$ . (3) Proceed to perform conventional inference using the normality result (2.10).

The following algorithm is only invoked if the weak instruments problem has been diagnosed, e.g., using the methods of Stock and Yogo (2005). In the algorithm below,  $\mathcal{A}_1$  is the parameter space, and  $\mathcal{G}_1 \subset \mathcal{A}_1$  is a grid of potential values for  $\alpha_1$ . Choose the confidence level  $1 - \gamma$  of the interval, and set  $\Lambda(1 - \gamma) = c\sqrt{n}\Phi^{-1}(1 - \gamma/2p)$ .

**Algorithm A.3** (IV Inference Robust to Weak Identification). (1) Set  $\mathcal{C} = \emptyset$ . (2) For each  $a \in \mathcal{G}_1$  compute  $\Lambda_a$  as in (4.19). If  $\Lambda_a \leq \Lambda(1 - \gamma)$  add  $a$  to  $\mathcal{C}$ . (3) Report  $\mathcal{C}$ .

## APPENDIX B. TOOLS

The following useful lemma is a consequence of moderate deviations theorems for self-normalized sums in Jing, Shao, and Wang (2003) and de la Peña, Lai, and Shao (2009).

We shall be using the following result – Theorem 7.4 in de la Peña, Lai, and Shao (2009). Let  $X_1, \dots, X_n$  be independent, zero-mean variables, and  $S_n = \sum_{i=1}^n X_i$ ,  $V_n^2 = \sum_{i=1}^n X_i^2$ . For  $0 < \mu \leq 1$  set  $B_n^2 = \sum_{i=1}^n \mathbb{E}X_i^2$ ,  $L_{n,\mu} = \sum_{i=1}^n \mathbb{E}|X_i|^{2+\mu}$ ,  $d_{n,\mu} = B_n/L_{n,\mu}^{1/(2+\mu)}$ . Then uniformly in  $0 \leq x \leq d_{n,\mu}$ ,

$$\frac{\mathbb{P}(S_n/V_n \geq x)}{\bar{\Phi}(x)} = 1 + O(1) \left( \frac{1+x}{d_{n,\mu}} \right)^{2+\mu}, \quad \frac{\mathbb{P}(S_n/V_n \leq -x)}{\Phi(-x)} = 1 + O(1) \left( \frac{1+x}{d_{n,\mu}} \right)^{2+\mu},$$

where the terms  $O(1)$  are bounded in absolute value by a universal constant  $A$ ,  $\bar{\Phi} := 1 - \Phi$ , and  $\Phi$  is the cumulative distribution function of a standard Gaussian random variable.

**Lemma 5** (Moderate Deviation Inequality for Maximum of a Vector). *Suppose that*

$$\mathcal{S}_j = \frac{\sum_{i=1}^n U_{ij}}{\sqrt{\sum_{i=1}^n U_{ij}^2}},$$

where  $U_{ij}$  are independent variables across  $i$  with mean zero. We have that

$$\mathbb{P} \left( \max_{1 \leq j \leq p} |\mathcal{S}_j| > \Phi^{-1}(1 - \gamma/2p) \right) \leq \gamma \left( 1 + \frac{A}{\ell_n^3} \right),$$

where  $A$  is an absolute constant, provided that for  $\ell_n > 0$

$$0 \leq \Phi^{-1}(1 - \gamma/(2p)) \leq \frac{n^{1/6}}{\ell_n} \min_{1 \leq j \leq p} M[U_j] - 1, \quad M[U_j] := \frac{\left( \frac{1}{n} \sum_{i=1}^n EU_{ij}^2 \right)^{1/2}}{\left( \frac{1}{n} \sum_{i=1}^n E|U_{ij}|^3 \right)^{1/3}}.$$

*Proof of Lemma 5.* Step 1. We first note the following simple consequence of the result of Theorem 7.4 in de la Peña, Lai, and Shao (2009). Let  $X_{1,n}, \dots, X_{n,n}$  be the triangular array of i.n.i.d, zero-mean random variables. Suppose that

$$n^{1/6} M_n / \ell_n \geq 1, \quad M_n := \frac{\left( \frac{1}{n} \sum_{i=1}^n EX_{i,n}^2 \right)^{1/2}}{\left( \frac{1}{n} \sum_{i=1}^n E|X_{i,n}|^3 \right)^{1/3}}.$$

Then uniformly on  $0 \leq x \leq n^{1/6} M_n / \ell_n - 1$ , the quantities  $S_{n,n} = \sum_{i=1}^n X_{i,n}$  and  $V_{n,n}^2 = \sum_{i=1}^n X_{i,n}^2$  obey

$$\left| \frac{\mathbb{P}(|S_{n,n}/V_{n,n}| \geq x)}{2\Phi(x)} - 1 \right| \leq \frac{A}{\ell_n^3}.$$

This corollary follows by the application of the quoted theorem to the case with  $\mu = 1$ . The calculated error bound follows from the triangular inequalities and conditions on  $\ell_n$  and  $M_n$ .

Step 2. It follows that

$$\begin{aligned} & \mathbb{P} \left( \max_{1 \leq j \leq p} |\mathcal{S}_j| > \Phi^{-1}(1 - \gamma/2p) \right) \leq_{(1)} p \max_{1 \leq j \leq p} \mathbb{P} (|\mathcal{S}_j| > \Phi^{-1}(1 - \gamma/2p)) \\ & =_{(2)} p \mathbb{P} (|\mathcal{S}_{j_n}| > \Phi^{-1}(1 - \gamma/2p)) \leq_{(3)} p 2\bar{\Phi}(\Phi^{-1}(1 - \gamma/2p)) \left( 1 + \frac{A}{\ell_n^3} \right) \\ & \leq 2p\gamma/(2p) \left( 1 + \frac{A}{\ell_n^3} \right) \leq \gamma \left( 1 + \frac{A}{\ell_n^3} \right), \end{aligned}$$

on the set  $0 \leq \Phi^{-1}(1 - \gamma/(2p)) \leq \frac{n^{1/6}}{\ell_n} M_{j_n} - 1$ , where inequality (1) follows by the union bound, equality (2) is the maximum taken over finite set, so the maximum is attained at some  $j_n \in \{1, \dots, p\}$ , and the last inequality follows by the application of Step 1, by setting  $X_{i,n} = U_{i,j_n}$ .  $\square$

## APPENDIX C. PROOF OF THEOREM 1

The proof of Theorem 1 has four steps. The most important steps are the Steps 1-3. One half of Step 1 for bounding  $\|\cdot\|_{2,n}$ -rate follows the strategy of Bickel, Ritov, and Tsybakov (2009), but accommodates data-driven penalty loadings. The other half of Step 1 for bounding the  $\|\cdot\|_1$ -rate is new for the nonparametric case. Step 2 innovatively uses the moderate deviation theory for self-normalized sums which allows us to obtain sharp results for non-Gaussian and heteroscedastic errors as well as handle data-driven penalty loadings. Step 3 relates the ideal penalty loadings and the feasible penalty loadings. Step 4 puts the results together to reach the conclusions.

Step 1. For  $C > 0$  and each  $l = 1, \dots, k_e$ , consider the following weighted restricted eigenvalue

$$\kappa_C^l = \min_{\delta \in \mathbb{R}^p: \|\hat{\Upsilon}_l^0 \delta_{T_l^c}\|_1 \leq C \|\hat{\Upsilon}_l^0 \delta_{T_l}\|_1, \|\delta\|_2 \neq 0} \frac{\sqrt{s} \|f'_i \delta\|_{2,n}}{\|\hat{\Upsilon}_l^0 \delta_{T_l}\|_1}.$$

This quantity controls the modulus of continuity between the prediction norm  $\|f'_i \delta\|_{2,n}$  and the  $\ell_1$ -norm  $\|\delta\|_1$  within a restricted region that depends on  $l = 1, \dots, k_e$ . Note that if  $a = \min_{1 \leq l \leq k_e} \min_{1 \leq j \leq p} \hat{\Upsilon}_{lj}^0 \leq \max_{1 \leq l \leq k_e} \|\hat{\Upsilon}_l^0\|_\infty = b$ , for every  $C > 0$ , because  $\{\delta \in \mathbb{R}^p : \|\hat{\Upsilon}_l^0 \delta_{T_l^c}\|_1 \leq C \|\hat{\Upsilon}_l^0 \delta_{T_l}\|_1\} \subseteq \{\delta \in \mathbb{R}^p : a \|\delta_{T_l^c}\|_1 \leq bC \|\delta_{T_l}\|_1\}$  and  $\|\hat{\Upsilon}_l^0 \delta_{T_l}\|_1 \leq b \|\delta_{T_l}\|_1$ , we have

$$\min_{1 \leq l \leq k_e} \kappa_C^l \geq (1/b) \kappa_{(bC/a)}(\mathbb{E}_n[f_i f'_i])$$

where the latter is the restricted eigenvalue defined in (3.12). If  $C = c_0 = (uc + 1)/(\ell c - 1)$  we have  $\min_{1 \leq l \leq k_e} \kappa_{c_0}^l \geq (1/b) \kappa_{\bar{C}}(\mathbb{E}_n[f_i f'_i])$ . By Condition RF and by Step 3 of Appendix C below, we have  $a$  bounded away from zero and  $b$  bounded from above with probability approaching one as  $n$  increases.

The main result of this step is the following lemma:

**Lemma 6.** *Under Condition AS, if  $\lambda/n \geq c \|S_l\|_\infty$ , and  $\hat{\Upsilon}_l$  satisfies (3.13) with  $u \geq 1 \geq \ell > 1/c$  then*

$$\|f'_i(\hat{\beta}_l - \beta_{l0})\|_{2,n} \leq \left(u + \frac{1}{c}\right) \frac{\lambda \sqrt{s}}{n \kappa_{c_0}^l} + 2c_s,$$

$$\|\hat{\Upsilon}_l^0(\hat{\beta}_l - \beta_{l0})\|_1 \leq 3c_0 \frac{\sqrt{s}}{\kappa_{2c_0}^l} \left( \left(u + [1/c]\right) \frac{\lambda \sqrt{s}}{n \kappa_{c_0}^l} + 2c_s \right) + \frac{3c_0 n}{\lambda} c_s^2,$$

where  $c_0 = (uc + 1)/(\ell c - 1)$ .

*Proof of Lemma 6.* Let  $\delta_l := \hat{\beta}_l - \beta_{l0}$ . By optimality of  $\hat{\beta}_l$  we have

$$\hat{Q}_l(\hat{\beta}_l) - \hat{Q}_l(\beta_{l0}) \leq \frac{\lambda}{n} \left( \|\hat{\Upsilon}_l \beta_{l0}\|_1 - \|\hat{\Upsilon}_l \hat{\beta}_l\|_1 \right). \quad (\text{C.22})$$

Expanding the quadratic function  $\widehat{Q}_l$ , and using that  $S_l = 2(\widehat{\Upsilon}_l^0)^{-1}\mathbb{E}_n[v_{il}f_i]$ , we have

$$\begin{aligned} \left| \widehat{Q}_l(\widehat{\beta}_l) - \widehat{Q}_l(\beta_{l0}) - \|f'_i\delta_l\|_{2,n}^2 \right| &= |2\mathbb{E}_n[v_{il}f'_i\delta_l] + 2\mathbb{E}_n[a_{il}f'_i\delta_l]| \\ &\leq \|S_l\|_\infty \|\widehat{\Upsilon}_l^0\delta_l\|_1 + 2c_s \|f'_i\delta_l\|_{2,n}. \end{aligned} \quad (\text{C.23})$$

So combining (C.22) and (C.23) with  $\lambda/n \geq c\|S_l\|_\infty$  and the conditions imposed on  $\widehat{\Upsilon}_l$  in the statement of the theorem,

$$\begin{aligned} \|f'_i\delta_l\|_{2,n}^2 &\leq \frac{\lambda}{n} \left( \|\widehat{\Upsilon}_l\delta_{lT_l}\|_1 - \|\widehat{\Upsilon}_l\delta_{lT_l^c}\|_1 \right) + \|S_l\|_\infty \|\widehat{\Upsilon}_l^0\delta_l\|_1 + 2c_s \|f'_i\delta_l\|_{2,n} \\ &\leq \left( u + \frac{1}{c} \right) \frac{\lambda}{n} \|\widehat{\Upsilon}_l^0\delta_{lT_l}\|_1 - \left( \ell - \frac{1}{c} \right) \frac{\lambda}{n} \|\widehat{\Upsilon}_l^0\delta_{lT_l^c}\|_1 + 2c_s \|f'_i\delta_l\|_{2,n}. \end{aligned} \quad (\text{C.24})$$

To show the first statement of the Lemma we can assume  $\|f'_i\delta_l\|_{2,n} \geq 2c_s$ , otherwise we are done. This condition together with relation (C.24) implies that for  $c_0 = (uc+1)/(\ell c-1)$  we have  $\|\widehat{\Upsilon}_l^0\delta_{lT_l^c}\|_1 \leq c_0 \|\widehat{\Upsilon}_l^0\delta_{lT_l}\|_1$ . Therefore, by definition of  $\kappa_{c_0}^l$ , we have  $\|\widehat{\Upsilon}_l^0\delta_{lT_l}\|_1 \leq \sqrt{s} \|f'_i\delta_l\|_{2,n} / \kappa_{c_0}^l$ . Thus, relation (C.24) implies  $\|f'_i\delta_l\|_{2,n}^2 \leq (u + \frac{1}{c}) \frac{\lambda\sqrt{s}}{n\kappa_{c_0}^l} \|f'_i\delta_l\|_{2,n} + 2c_s \|f'_i\delta_l\|_{2,n}$  and the result follows.

To establish the second statement of the Lemma, we consider two cases. First, assume  $\|\widehat{\Upsilon}_l^0\delta_{lT_l^c}\|_1 \leq 2c_0 \|\widehat{\Upsilon}_l^0\delta_{lT_l}\|_1$ . In this case, by definition of  $\kappa_{2c_0}^l$ , we have

$$\|\widehat{\Upsilon}_l^0\delta_l\|_1 \leq (1 + 2c_0) \|\widehat{\Upsilon}_l^0\delta_{lT_l}\|_1 \leq (1 + 2c_0) \sqrt{s} \|f'_i\delta_l\|_{2,n} / \kappa_{2c_0}^l$$

and the result follows by applying the first bound to  $\|f'_i\delta_l\|_{2,n}$ . On the other hand, consider the case that

$$\|\widehat{\Upsilon}_l^0\delta_{lT_l^c}\|_1 > 2c_0 \|\widehat{\Upsilon}_l^0\delta_{lT_l}\|_1 \quad (\text{C.25})$$

which would already imply  $\|f'_i\delta_l\|_{2,n} \leq 2c_s$  by (C.24). Moreover,

$$\begin{aligned} \|\widehat{\Upsilon}_l^0\delta_{lT_l^c}\|_1 &\leq_{(1)} c_0 \|\widehat{\Upsilon}_l^0\delta_{lT_l}\|_1 + \frac{c}{\ell c-1} \frac{n}{\lambda} \|f'_i\delta_l\|_{2,n} (2c_s - \|f'_i\delta_l\|_{2,n}) \\ &\leq_{(2)} c_0 \|\widehat{\Upsilon}_l^0\delta_{lT_l}\|_1 + \frac{c}{\ell c-1} \frac{n}{\lambda} c_s^2 \leq_{(3)} \frac{1}{2} \|\widehat{\Upsilon}_l^0\delta_{lT_l^c}\|_1 + \frac{c}{\ell c-1} \frac{n}{\lambda} c_s^2, \end{aligned}$$

where (1) holds by (C.24), (2) holds since  $\|f'_i\delta_l\|_{2,n} (2c_s - \|f'_i\delta_l\|_{2,n}) \leq \max_{x \geq 0} x(2c_s - x) \leq c_s^2$ , and (3) follows from (C.25). Thus,

$$\|\widehat{\Upsilon}_l^0\delta_l\|_1 \leq \left( 1 + \frac{1}{2c_0} \right) \|\widehat{\Upsilon}_l^0\delta_{lT_l^c}\|_1 \leq \left( 1 + \frac{1}{2c_0} \right) \frac{2c}{\ell c-1} \frac{n}{\lambda} c_s^2,$$

and the result follows from noting that  $c/(\ell c-1) \leq c_0/u \leq c_0$  and  $1 + 1/2c_0 \leq 3/2$ .  $\square$

**Step 2.** In this step we prove a lemma about the quantiles of the maximum of the scores  $S_l = 2\mathbb{E}_n[(\widehat{\Upsilon}_l^0)^{-1}f_i v_{il}]$ , and use it to pin down the level of the penalty. For  $\lambda = c2\sqrt{n}\Phi^{-1}(1-\gamma/(2k_e p))$ , we have that as  $\gamma \rightarrow 0$  and  $n \rightarrow \infty$ ,  $P(c \max_{1 \leq l \leq k_e} n\|S_l\|_\infty > \lambda) = o(1)$ , provided that for some  $b_n \rightarrow \infty$

$$2\Phi^{-1}(1-\gamma/(2k_e p)) \leq \frac{n^{1/6}}{b_n} \min_{1 \leq j \leq p, 1 \leq l \leq k_e} M_{jl}, \quad M_{jl} := \frac{\bar{\mathbb{E}}[f_{ij}^2 v_{il}^2]^{1/2}}{\bar{\mathbb{E}}[|f_{ij}|^3 |v_{il}|^3]^{1/3}}.$$

Note that the last condition is satisfied under our conditions for large  $n$  for some  $b_n \rightarrow \infty$ , since  $k_e$  is fixed,  $\log(1/\gamma) \lesssim \log(p \vee n)$ ,  $K_n^2 \log^3(p \vee n) = o(n)$ , and  $\min_{1 \leq j \leq p, 1 \leq l \leq k_e} M_{jl} \gtrsim 1/K_n^{1/3}$ . This result follows from the bounds on moderate deviations of a maximum of a vector provided in Lemma 5, by  $\bar{\Phi}(t) \leq \phi(t)/t$ ,  $\max_{j \leq p, l \leq k_e} 1/M_{jl} \lesssim K_n^{1/3}$ , and  $K_n^{2/3} \log(p \vee n) = o(n^{1/3})$  holding by Condition RF.

Step 3. The main result of this step is the following: Define the expected “ideal” penalty loadings  $\Upsilon_l^0 := \text{diag} \left( \sqrt{\bar{\mathbb{E}}[f_{i1}^2 v_{il}^2]}, \dots, \sqrt{\bar{\mathbb{E}}[f_{ip}^2 v_{il}^2]} \right)$ , where the entries of  $\Upsilon_l^0$  are bounded away from zero and from above uniformly in  $n$  by Condition RF. Then the empirical “ideal” loadings converge to the expected “ideal” loadings:  $\max_{1 \leq l \leq k_e} \|\hat{\Upsilon}_l^0 - \Upsilon_l^0\|_\infty \rightarrow_P 0$ . This is assumed in Condition RF.

Step 4. Combining the results of all the steps above, given that  $\lambda = 2c\sqrt{n}\Phi^{-1}(1 - \gamma/(2pk_e)) \lesssim c\sqrt{n \log(pk_e/\gamma)}$ ,  $k_e$  fixed, and asymptotic valid penalty loadings  $\hat{\Upsilon}_l$ , and using the bound  $c_s \lesssim_P \sqrt{s/n}$  from Condition AS, we obtain the conclusion that

$$\|f'_i(\hat{\beta}_l - \beta_{l0})\|_{2,n} \lesssim_P \frac{1}{\kappa_{c_0}^l} \sqrt{\frac{s \log(k_e p / \gamma)}{n}} + \sqrt{\frac{s}{n}},$$

which gives, by the triangular inequality and by  $\|D_{il} - f'_i \beta_{l0}\|_{2,n} \leq c_s \lesssim_P \sqrt{s/n}$  holding by Condition AS,

$$\|\hat{D}_{il} - D_{il}\|_{2,n} \lesssim_P \frac{1}{\kappa_{c_0}^l} \sqrt{\frac{s \log(k_e p / \gamma)}{n}}.$$

The first result follows since  $\kappa_{\bar{C}} \lesssim_P \kappa_{c_0}^l$  by Step 1.

To derive the  $\ell_1$ -rate we apply the second result in Lemma 6 as follows

$$\begin{aligned} \|\hat{\beta}_l - \beta_{l0}\|_1 &\leq \|(\hat{\Upsilon}_l^0)^{-1}\|_\infty \|\hat{\Upsilon}_l^0(\hat{\beta}_l - \beta_{l0})\|_1 \\ &\lesssim_P \|(\hat{\Upsilon}_l^0)^{-1}\|_\infty \left( \frac{\sqrt{s}}{\kappa_{2c_0}^l} \left( \frac{1}{\kappa_{c_0}^l} \sqrt{\frac{s \log(k_e p / \gamma)}{n}} + \sqrt{\frac{s}{n}} \right) + \frac{1}{\sqrt{\log(p/\gamma)}} \frac{s}{\sqrt{n}} \right) \lesssim_P \frac{1}{(\kappa_{2c_0}^l)^2} \sqrt{\frac{s^2 \log(k_e p / \gamma)}{n}}. \end{aligned}$$

That yields the result since  $\kappa_{2\bar{C}} \lesssim_P \kappa_{2c_0}^l$  by Step 1.  $\square$

## APPENDIX D. PROOF OF THEOREM 2

The proof proceeds in three steps. The general strategy of Step 1 follows Belloni and Chernozhukov (2011a) and Belloni and Chernozhukov (2012), but a major difference is the use of moderate deviation theory for self-normalized sums which allows us to obtain the results for non-Gaussian and heteroscedastic errors as well as handle data-driven penalty loadings. The sparsity proofs are motivated by Belloni and Chernozhukov (2012) but adjusted for the data-driven penalty loadings that contain self-normalizing factors.

Step 1. Here we derive a general performance bound for Post-Lasso, that actually contains more information than the statement of the theorem. This lemma will be invoked in Step 3 below.

Let  $F = [f_1; \dots; f_n]'$  denote a  $n$  by  $p$  matrix and for a set of indices  $S \subset \{1, \dots, p\}$  we define  $\mathcal{P}_S = F[S](F[S]'F[S])^{-1}F[S]'$  denote the projection matrix on the columns associated with the indices in  $S$ .

**Lemma 7** (Performance of the Post-Lasso). *Under Conditions AS and RF, let  $\hat{T}_l$  denote the support selected by  $\hat{\beta}_l = \hat{\beta}_{lL}$ ,  $\hat{T}_l \subseteq \hat{I}_l$ ,  $\tilde{m}_l = |\hat{I}_l \setminus T_l|$ , and  $\hat{\beta}_{lPL}$  be the Post-Lasso estimator based on  $\hat{I}_l$ ,  $l = 1, \dots, k_e$ . Then we have*

$$\begin{aligned} \max_{l \leq k_e} \|D_{il} - f'_i \hat{\beta}_{lPL}\|_{2,n} &\lesssim_P \sqrt{\frac{s}{n}} \sqrt{\frac{k_e \wedge \log(sk_e)}{\phi_{\min}(s)}} + \max_{l \leq k_e} \frac{\sqrt{\tilde{m}_l \log(pk_e)}}{\sqrt{n} \phi_{\min}(\tilde{m}_l)} + \|(D_l - \mathcal{P}_{\hat{I}_l} D_l)/\sqrt{n}\|_2, \\ \max_{1 \leq l \leq k_e} \|\hat{\Upsilon}_l(\hat{\beta}_{lPL} - \beta_{l0})\|_1 &\leq \max_{1 \leq l \leq k_e} \frac{\left(\|\hat{\Upsilon}_l^0\|_\infty + \|\hat{\Upsilon}_l - \hat{\Upsilon}_l^0\|_\infty\right) \sqrt{\tilde{m}_l + s}}{\sqrt{\phi_{\min}(\tilde{m}_l + s)}} \|f'_i(\hat{\beta}_{lPL} - \beta_{l0})\|_{2,n}. \end{aligned}$$

If in addition  $\lambda/n \geq c\|S_l\|_\infty$ , and  $\hat{\Upsilon}_l$  satisfies (3.13) with  $u \geq 1 \geq \ell > 1/c$  in the first stage for Lasso for every  $l = 1, \dots, k_e$ , then we have

$$\max_{l \leq k_e} \|(D_l - \mathcal{P}_{\hat{I}_l} D_l)/\sqrt{n}\|_2 \leq \max_{l \leq k_e} \left(u + \frac{1}{c}\right) \frac{\lambda\sqrt{s}}{n\kappa_{c_0}^l} + 3c_s.$$

*Proof of Lemma 7.* We have that  $D_l - F\hat{\beta}_{lPL} = (I - \mathcal{P}_{\hat{I}_l})D_l - \mathcal{P}_{\hat{I}_l} v_l$  where  $I$  is the identity operator. Therefore for every  $l = 1, \dots, k_e$  we have

$$\|D_l - F\hat{\beta}_{lPL}\|_2 \leq \|(I - \mathcal{P}_{\hat{I}_l})D_l\|_2 + \|\mathcal{P}_{T_l} v_l\|_2 + \|\mathcal{P}_{\hat{I}_l \setminus T_l} v_l\|_2. \quad (\text{D.26})$$

Since  $\|F[\hat{I}_l \setminus T_l]/\sqrt{n}(F[\hat{I}_l \setminus T_l]'F[\hat{I}_l \setminus T_l]/n)^{-1}\| \leq \sqrt{1/\phi_{\min}(\tilde{m}_l)}$ ,  $\tilde{m}_l = |\hat{I}_l \setminus T_l|$ , the last term in (D.26) satisfies

$$\|\mathcal{P}_{\hat{I}_l \setminus T_l} v_l\|_2 \leq \sqrt{1/\phi_{\min}(\tilde{m}_l)} \|F[\hat{I}_l \setminus T_l]' v_l / \sqrt{n}\|_2 \leq \sqrt{\tilde{m}_l / \phi_{\min}(\tilde{m}_l)} \|F' v_l / \sqrt{n}\|_\infty.$$

Under Condition RF, by Lemma 5 we have

$$\max_{l=1, \dots, k_e} \|F' v_l / \sqrt{n}\|_\infty \lesssim_P \sqrt{\log(pk_e)} \max_{l \leq k_e, j \leq p} \sqrt{\mathbb{E}_n[f_{ij}^2 v_{il}^2]}.$$

Note that Condition RF also implies  $\max_{l \leq k_e, j \leq p} \sqrt{\mathbb{E}_n[f_{ij}^2 v_{il}^2]} \lesssim_P 1$  since  $\max_{l \leq k_e, j \leq p} |(\mathbb{E}_n - \bar{\mathbb{E}})[f_{ij}^2 v_{il}^2]| \rightarrow_P 0$  and  $\max_{l \leq k_e, j \leq p} \bar{\mathbb{E}}[f_{ij}^2 v_{il}^2] \leq \max_{l \leq k_e, j \leq p} \bar{\mathbb{E}}[f_{ij}^2 \tilde{d}_{il}^2] \lesssim 1$ .

We bound the second term in (D.26) in two ways. First, proceeding as above we have

$$\max_{l=1, \dots, k_e} \|\mathcal{P}_{T_l} v_l\|_2 \lesssim_P \sqrt{\log(k_e s)} \sqrt{s/\phi_{\min}(s)} \max_{l \leq k_e, j \leq p} \sqrt{\mathbb{E}_n[f_{ij}^2 v_{il}^2]}.$$

Second, since  $E[\|F[T_l]'v_l\|_2^2] = E[\sum_{j \in T_l} (\sum_{i=1}^n f_{ij}v_{il})^2] = \sum_{j \in T_l} \sum_{i=1}^n E[f_{ij}^2 v_{il}^2]$ , we have

$$\max_{l=1, \dots, k_e} \|\mathcal{P}_{T_l} v_l\|_2 \lesssim_P \sqrt{sk_e/\phi_{\min}(s)} \max_{l \leq k_e, j \leq p} \sqrt{E[f_{ij}^2 v_{il}^2]}.$$

These relations yield the first result.

Letting  $\delta_l = \hat{\beta}_{lPL} - \beta_{l0}$ , the statement regarding the  $\ell_1$ -norm of the theorem follows from

$$\|\hat{\Upsilon}_l \delta_l\|_1 \leq \|\hat{\Upsilon}_l\|_\infty \|\delta_l\|_1 \leq \|\hat{\Upsilon}_l\|_\infty \sqrt{\|\delta_l\|_0} \|\delta_l\|_2 \leq \|\hat{\Upsilon}_l\|_\infty \sqrt{\|\delta_l\|_0} \|f'_l \delta_l\|_{2,n} / \sqrt{\phi_{\min}(\|\delta_l\|_0)},$$

and noting that  $\|\delta_l\|_0 \leq \tilde{m}_l + s$  and  $\|\hat{\Upsilon}_l\|_\infty \leq \|\hat{\Upsilon}_l^0\|_\infty + \|\hat{\Upsilon}_l - \hat{\Upsilon}_l^0\|_\infty$ .

The last statement follows from noting that the Lasso solution provides an upper bound to the approximation of the best model based on  $\hat{T}_l$ , since  $\hat{T}_l \subseteq \hat{I}_l$ , and the application of Lemma 6.  $\square$

**Comment D.1** (Comparison between Lasso and Post-Lasso performance). Under mild conditions on the empirical Gram matrix and on the number of additional variables, Lemma 10 below derives sparsity bounds on the model selected by Lasso, which establishes that

$$|\hat{T}_l \setminus T_l| = \hat{m}_l \lesssim_P s.$$

Under this condition, we have that the rate of Post-Lasso is no worse than Lasso's rate. This occurs despite the fact that Lasso may in general fail to correctly select the oracle model  $T_l$  as a subset, that is  $T_l \not\subseteq \hat{T}_l$ . However, if the oracle model has well-separated coefficients and the approximation error does not dominate the estimation error, then the Post-Lasso rate improves upon Lasso's rate. Specifically, this occurs if Condition AS holds,  $\hat{m}_l = o_P(s)$  and  $T_l \subseteq \hat{T}_l$  wp  $\rightarrow 1$ , or if  $T = \hat{T}$  wp  $\rightarrow 1$  as under the conditions of Wainwright (2009). In such cases, the rates found for Lasso are sharp, and they cannot be faster than  $\sqrt{s \log p/n}$ . Thus, the improvement in the rate of convergence of Post-Lasso over Lasso is strict these cases. Note that, as shown in the proof of Lemma 8, a higher penalty level will tend to reduce  $\hat{m}_l$  but will increase the likelihood of  $T_l \not\subseteq \hat{T}_l$ . On the other hand, a lower penalty level will decrease the likelihood of  $T_l \not\subseteq \hat{T}_l$  (bias) but will tend to increase  $\hat{m}_l$  (variance). The impact in the estimation of this trade off is captured by the last term of the bound in Lemma 7.

Step 2. In this step we provide a sparsity bound for Lasso, which is important for establishing various rate results and fundamental to the analysis of Post-Lasso. It relies on the following lemmas.

**Lemma 8** (Empirical pre-sparsity for Lasso). *Let  $\hat{T}_l$  denote the support selected by the Lasso estimator,  $\hat{m}_l = |\hat{T}_l \setminus T_l|$ , and assume that  $\lambda/n \geq c\|S_l\|_\infty$  and  $u \geq 1 \geq \ell > 1/c$  as in Lemma 6. Then, for  $c_0 = (uc + 1)/(\ell c - 1)$  we have*

$$\sqrt{\hat{m}_l} \leq \sqrt{\phi_{\max}(\hat{m}_l)} \|(\hat{\Upsilon}_l^0)^{-1}\|_\infty c_0 \left[ \frac{2\sqrt{s}}{\kappa_{c_0}^l} + \frac{6nc_s}{\lambda} \right].$$

*Proof of Lemma 8.* We have from the optimality conditions that the Lasso estimator  $\hat{\beta}_l = \hat{\beta}_{lL}$  satisfies

$$2\mathbb{E}_n[\hat{\Upsilon}_{lj}^{-1} f_{ij}(y_i - f'_i \hat{\beta}_l)] = \text{sign}(\hat{\beta}_{lj})\lambda/n \quad \text{for each } j \in \hat{T}_l \setminus T_l.$$

Therefore, noting that  $\|\hat{\Upsilon}_l^{-1} \hat{\Upsilon}_l^0\|_\infty \leq 1/\ell$ , we have for  $R = (a_{l1}, \dots, a_{ln})'$  and  $F$  denoting the  $n \times p$  matrix with rows  $f'_i$ ,  $i = 1, \dots, n$

$$\begin{aligned} \sqrt{\hat{m}_l} \lambda &= 2\|(\hat{\Upsilon}_l^{-1} F'(Y - F\hat{\beta}_l))_{\hat{T}_l \setminus T_l}\|_2 \\ &\leq 2\|(\hat{\Upsilon}_l^{-1} F'(Y - R - F\beta_{l0}))_{\hat{T}_l \setminus T_l}\|_2 + 2\|(\hat{\Upsilon}_l^{-1} F'R)_{\hat{T}_l \setminus T_l}\|_2 + 2\|(\hat{\Upsilon}_l^{-1} F'F(\beta_{l0} - \hat{\beta}_l))_{\hat{T}_l \setminus T_l}\|_2 \\ &\leq \sqrt{\hat{m}_l} n \|\hat{\Upsilon}_l^{-1} \hat{\Upsilon}_l^0\|_\infty \|S_l\|_\infty + 2n\sqrt{\phi_{\max}(\hat{m}_l)} \|\hat{\Upsilon}_l^{-1}\|_\infty c_s + 2n\sqrt{\phi_{\max}(\hat{m}_l)} \|\hat{\Upsilon}_l^{-1}\|_\infty \|f'_i(\hat{\beta}_l - \beta_{l0})\|_{2,n}, \\ &\leq \sqrt{\hat{m}_l} (1/\ell) n \|S_l\|_\infty + 2n\sqrt{\phi_{\max}(\hat{m}_l)} \frac{\|(\hat{\Upsilon}_l^0)^{-1}\|_\infty}{\ell} c_s + 2n\sqrt{\phi_{\max}(\hat{m}_l)} \frac{\|(\hat{\Upsilon}_l^0)^{-1}\|_\infty}{\ell} \|f'_i(\hat{\beta}_l - \beta_{l0})\|_{2,n}, \end{aligned}$$

where we used that

$$\begin{aligned} &\|(F'F(\beta_{l0} - \hat{\beta}_l))_{\hat{T}_l \setminus T_l}\|_2 \\ &= \sup_{\|\delta\|_0 \leq \hat{m}_l, \|\delta\|_2 \leq 1} |\delta' F' F(\beta_{l0} - \hat{\beta}_l)| \leq \sup_{\|\delta\|_0 \leq \hat{m}_l, \|\delta\|_2 \leq 1} \|\delta' F'\|_2 \|F(\beta_{l0} - \hat{\beta}_l)\|_2 \\ &\leq \sup_{\|\delta\|_0 \leq \hat{m}_l, \|\delta\|_2 \leq 1} \sqrt{|\delta' F' F \delta|} \|F(\beta_{l0} - \hat{\beta}_l)\|_2 \leq n\sqrt{\phi_{\max}(\hat{m}_l)} \|f'_i(\beta_{l0} - \hat{\beta}_l)\|_{2,n}, \end{aligned}$$

and similarly

$$\begin{aligned} \|(F'R)_{\hat{T}_l \setminus T_l}\|_2 &= \sup_{\|\delta\|_0 \leq \hat{m}_l, \|\delta\|_2 \leq 1} |\delta' F' R| \leq \sup_{\|\delta\|_0 \leq \hat{m}_l, \|\delta\|_2 \leq 1} \|\delta' F'\|_2 \|R\|_2 \\ &= \sup_{\|\delta\|_0 \leq \hat{m}_l, \|\delta\|_2 \leq 1} \sqrt{|\delta' F' F \delta|} \|R\|_2 \leq n\sqrt{\phi_{\max}(\hat{m}_l)} c_s. \end{aligned}$$

Since  $\lambda/c \geq n\|S_l\|_\infty$ , and by Lemma 6,  $\|f'_i(\hat{\beta}_l - \beta_{l0})\|_{2,n} \leq (u + \frac{1}{c}) \frac{\lambda\sqrt{s}}{n\kappa_{c_0}^l} + 2c_s$  we have

$$\sqrt{\hat{m}_l} \leq \frac{2\sqrt{\phi_{\max}(\hat{m}_l)} \frac{\|(\hat{\Upsilon}_l^0)^{-1}\|_\infty}{\ell} \left[ (u + \frac{1}{c}) \frac{\sqrt{s}}{\kappa_{c_0}^l} + \frac{3nc_s}{\lambda} \right]}{(1 - \frac{1}{c\ell})}.$$

The result follows by noting that  $(u + [1/c])/(1 - 1/[c\ell]) = c_0\ell$  by definition of  $c_0$ .  $\square$

**Lemma 9** (Sub-linearity of maximal sparse eigenvalues). *Let  $M$  be a semi-definite positive matrix. For any integer  $k \geq 0$  and constant  $\ell \geq 1$  we have  $\phi_{\max}(\lceil \ell k \rceil)(M) \leq \lceil \ell \rceil \phi_{\max}(k)(M)$ .*

*Proof.* Denote by  $\phi_M(k) = \phi_{\max}(k)(M)$ , and let  $\bar{\alpha}$  achieve  $\phi_M(\ell k)$ . Moreover let  $\sum_{i=1}^{\lceil \ell \rceil} \alpha_i = \bar{\alpha}$  such that  $\sum_{i=1}^{\lceil \ell \rceil} \|\alpha_i\|_0 = \|\bar{\alpha}\|_0$ . We can choose  $\alpha_i$ 's such that  $\|\alpha_i\|_0 \leq k$  since  $\lceil \ell \rceil k \geq \ell k$ . Since  $M$  is positive semi-definite, for any  $i, j$  w  $\alpha'_i M \alpha_i + \alpha'_j M \alpha_j \geq 2|\alpha'_i M \alpha_j|$ . Therefore

$$\begin{aligned} \phi_M(\ell k) &= \bar{\alpha}' M \bar{\alpha} = \sum_{i=1}^{\lceil \ell \rceil} \alpha'_i M \alpha_i + \sum_{i=1}^{\lceil \ell \rceil} \sum_{j \neq i} \alpha'_i M \alpha_j \leq \sum_{i=1}^{\lceil \ell \rceil} \{ \alpha'_i M \alpha_i + (\lceil \ell \rceil - 1) \alpha'_i M \alpha_i \} \\ &\leq \lceil \ell \rceil \sum_{i=1}^{\lceil \ell \rceil} \|\alpha_i\|^2 \phi_M(\|\alpha_i\|_0) \leq \lceil \ell \rceil \max_{i=1, \dots, \lceil \ell \rceil} \phi_M(\|\alpha_i\|_0) \leq \lceil \ell \rceil \phi_M(k) \end{aligned}$$

where we used that  $\sum_{i=1}^{\lceil \ell \rceil} \|\alpha_i\|^2 = 1$ .  $\square$



**Lemma 10** (Sparsity bound for Lasso under data-driven penalty). *Consider the Lasso estimator  $\hat{\beta}_l = \hat{\beta}_{lL}$  with  $\lambda/n \geq c\|S_l\|_\infty$ , and let  $\hat{m}_l = |\hat{T}_l \setminus T_l|$ . Consider the set*

$$\mathcal{M} = \left\{ m \in \mathbb{N} : m > s \, 2\phi_{\max}(m) \|(\hat{\Upsilon}_l^0)^{-1}\|_\infty^2 \left[ \frac{2c_0}{\kappa_{c_0}^l} + \frac{6c_0nc_s}{\lambda\sqrt{s}} \right]^2 \right\}.$$

Then,

$$\hat{m}_l \leq s \left( \min_{m \in \mathcal{M}} \phi_{\max}(m \wedge n) \right) \|(\hat{\Upsilon}_l^0)^{-1}\|_\infty^2 \left( \frac{2c_0}{\kappa_{c_0}^l} + \frac{6c_0nc_s}{\lambda\sqrt{s}} \right)^2.$$

**Comment D.2** (Sparsity Bound). Provided that the regularization event  $\lambda/n \geq c\|S_l\|_\infty$  occurs, Lemma 10 bounds the number of components  $\hat{m}_l$  incorrectly selected by Lasso. Essentially, the bound depends on  $s$  and on the ratio between the maximum sparse eigenvalues and the restricted eigenvalues. Thus, the empirical Gram matrix can impact the sparsity bound substantially. However, under Condition SE, the ratio mentioned is bounded from above uniformly in  $n$ . As expected the bound improves and the regularization event is more likely to occur if a larger value of the penalty parameter  $\lambda$  is used.

*Proof of Lemma 10.* Rewriting the conclusion in Lemma 8 we have

$$\hat{m}_l \leq s \, \phi_{\max}(\hat{m}_l) \|(\hat{\Upsilon}_l^0)^{-1}\|_\infty^2 \left[ \frac{2c_0}{\kappa_{c_0}^l} + \frac{6c_0nc_s}{\lambda\sqrt{s}} \right]^2. \quad (\text{D.27})$$

Note that  $\hat{m}_l \leq n$  by optimality conditions. Consider any  $M \in \mathcal{M}$ , and suppose  $\hat{m}_l > M$ . Therefore by Lemma 9 on sublinearity of sparse eigenvalues

$$\hat{m}_l \leq s \left\lceil \frac{\hat{m}_l}{M} \right\rceil \phi_{\max}(M) \|(\hat{\Upsilon}_l^0)^{-1}\|_\infty^2 \left[ \frac{2c_0}{\kappa_{c_0}^l} + \frac{6c_0nc_s}{\lambda\sqrt{s}} \right]^2.$$

Thus, since  $\lceil k \rceil \leq 2k$  for any  $k \geq 1$  we have

$$M \leq s \, 2\phi_{\max}(M) \|(\hat{\Upsilon}_l^0)^{-1}\|_\infty^2 \left[ \frac{2c_0}{\kappa_{c_0}^l} + \frac{6c_0nc_s}{\lambda\sqrt{s}} \right]^2$$

which violates the condition that  $M \in \mathcal{M}$ . Therefore, we have  $\hat{m}_l \leq M$ .

In turn, applying (D.27) once more with  $\hat{m}_l \leq (M \wedge n)$  we obtain

$$\hat{m}_l \leq s \, \phi_{\max}(M \wedge n) \|(\hat{\Upsilon}_l^0)^{-1}\|_\infty^2 \left[ \frac{2c_0}{\kappa_{c_0}^l} + \frac{6c_0nc_s}{\lambda\sqrt{s}} \right]^2.$$

The result follows by minimizing the bound over  $M \in \mathcal{M}$ . □

**Step 3.** Next we combine the previous steps to establish Theorem 2. As in Step 3 of Appendix C, recall that  $\max_{1 \leq l \leq k_e} \|\hat{\Upsilon}_l^0 - \Upsilon_l^0\|_\infty \rightarrow_P 0$ .

Let  $\bar{k}$  be the integer that achieve the minimum in the definition of  $\mu^2$ . Since  $c_s \lesssim_P \sqrt{s/n}$  leads to  $nc_s/[\lambda\sqrt{s}] \rightarrow_P 0$ , we have that  $\bar{k} \in \mathcal{M}$  with high probability as  $n \rightarrow \infty$ . Moreover, as long as

$\lambda/n \geq c \max_{1 \leq l \leq k_e} \|S_l\|_\infty$ ,  $\ell \rightarrow_P 1$  and  $c > 1$ , by Lemma 10 we have for every  $l = 1, \dots, k_e$  that

$$\hat{m}_l \lesssim_P s \mu^2 \phi_{\min}(\bar{k} + s) / \kappa_{\bar{C}}^2 \lesssim_P s \mu^2 \phi_{\min}(\hat{m}_l + s) / \kappa_{\bar{C}}^2 \quad (\text{D.28})$$

since  $\bar{k} \in \mathcal{M}$  implies  $\bar{k} \geq \hat{m}_l$ .

By the choice of  $\lambda = 2c\sqrt{n}\Phi^{-1}(1 - \gamma/(2pk_e))$  in (2.7), since  $\gamma \rightarrow 0$ , the event  $\lambda/n \geq c \max_{1 \leq l \leq k_e} \|S_l\|_\infty$  holds with probability approaching 1. Therefore, by the first and last results in Lemma 7 we have

$$\max_{1 \leq l \leq k_e} \|D_{il} - f'_i \hat{\beta}_{lPL}\|_{2,n} \lesssim_P \frac{\mu}{\kappa_{\bar{C}}} \sqrt{\frac{s \log p}{n}} + c_s + \max_{1 \leq l \leq k_e} \frac{\lambda \sqrt{s}}{n \kappa_{c_0}^l}.$$

Because  $\max_{1 \leq l \leq k_e} 1/\kappa_{c_0}^l \leq \max_{1 \leq l \leq k_e} \|\hat{\Gamma}_l^0\|_\infty / \kappa_{\bar{C}} \lesssim_P 1/\kappa_{\bar{C}}$  by Step 1 of Theorem 1, we have

$$\max_{1 \leq l \leq k_e} \|D_{il} - f'_i \hat{\beta}_{lPL}\|_{2,n} \lesssim_P \frac{\mu}{\kappa_{\bar{C}}} \sqrt{\frac{s \log(k_e p / \gamma)}{n}} \quad (\text{D.29})$$

since  $k_e \lesssim p$  and  $c_s \lesssim_P \sqrt{s/n}$ . That establishes the first inequality of Theorem 2.

To establish the second inequality of Theorem 2, since  $\|\hat{\beta}_{lPL} - \beta_{l0}\|_0 \leq \hat{m}_l + s$ , we have

$$\|\hat{\beta}_{lPL} - \beta_{l0}\|_1 \leq \sqrt{\|\hat{\beta}_{lPL} - \beta_{l0}\|_0} \|\hat{\beta}_{lPL} - \beta_{l0}\|_2 \leq \sqrt{\hat{m}_l + s} \frac{\|f'_i(\hat{\beta}_{lPL} - \beta_{l0})\|_{2,n}}{\sqrt{\phi_{\min}(\hat{m}_l + s)}}.$$

The sparsity bound (D.28), the prediction norm bound (D.29), and the relation  $\|D_{il} - f'_i \hat{\beta}_{lPL}\|_{2,n} \leq c_s + \|f'_i(\hat{\beta}_{lPL} - \beta_{l0})\|_{2,n}$  yield the result with the relation above.  $\square$

**Lemma 11** (Asymptotic Validity of the Data-Driven Penalty Loadings). *Under the conditions of Theorem 1 and Condition RF or the conditions of Theorem 2 and Condition SE, the penalty loadings  $\hat{\Upsilon}$  constructed by the K-step Algorithm A.1 are asymptotically valid. In particular, for  $K \geq 2$  we have  $u' = 1$ .*

For proof of Lemma 11 see Online Appendix.

## APPENDIX E. PROOFS OF LEMMAS 1-4

For proof of Lemma 1, see Belloni and Chernozhukov (2011a), Supplement. For proof of Lemma 2, see Belloni and Chernozhukov (2012). For proofs of Lemma 3 and 4, see Online Appendix.

## APPENDIX F. PROOFS OF THEOREMS 3-7.

**F.1. Proof of Theorems 3 and 4.** The proofs are original and they rely on the consistency of the sparsity-based estimators both with respect to the  $L^2(\mathbb{P}_n)$  norm  $\|\cdot\|_{2,n}$  and the  $\ell_1$ -norm  $\|\cdot\|_1$ . These proofs also exploit the use of moderate deviation theory for self-normalized sums.

Step 0. Using data-driven penalty satisfying (2.7) and (3.13), we have by Theorem 1 and Condition RE that the Lasso estimator and by Theorems 2 and Condition SE that the Post-Lasso estimator obey:

$$\max_{1 \leq l \leq k_e} \|\hat{D}_{il} - D_{il}\|_{2,n} \lesssim_P \sqrt{\frac{s \log(p \vee n)}{n}} \rightarrow 0 \quad (\text{F.30})$$

$$\sqrt{\log p} \|\hat{\beta}_l - \beta_{l0}\|_1 \lesssim_P \sqrt{\frac{s^2 \log^2(p \vee n)}{n}} \rightarrow 0. \quad (\text{F.31})$$

In order to prove Theorem 3 we need also the condition

$$\max_{1 \leq l \leq k_e} \|\hat{D}_{il} - D_{il}\|_{2,n}^2 n^{2/q_e} \lesssim_P \frac{s \log(p \vee n)}{n} n^{2/q_e} \rightarrow 0,$$

with the last statement holding by Condition SM. Note that Theorem 4 assumes (F.30)-(F.31) as high level conditions.

Step 1. We have that by  $\mathbb{E}[\epsilon_i | D_i] = 0$

$$\begin{aligned} \sqrt{n}(\hat{\alpha} - \alpha_0) &= \mathbb{E}_n[\hat{D}_i d'_i]^{-1} \sqrt{n} \mathbb{E}_n[\hat{D}_i \epsilon_i] = \{\mathbb{E}_n[\hat{D}_i d'_i]\}^{-1} (\mathbb{G}_n[D_i \epsilon_i] + o_P(1)) \\ &= \{\bar{\mathbb{E}}[D_i d'_i] + o_P(1)\}^{-1} (\mathbb{G}_n[D_i \epsilon_i] + o_P(1)), \end{aligned}$$

where by Steps 2 and 3 below:

$$\mathbb{E}_n[\hat{D}_i d'_i] = \bar{\mathbb{E}}[D_i d'_i] + o_P(1) \quad (\text{F.32})$$

$$\sqrt{n} \mathbb{E}_n[\hat{D}_i \epsilon_i] = \mathbb{G}_n[D_i \epsilon_i] + o_P(1) \quad (\text{F.33})$$

where  $\bar{\mathbb{E}}[D_i d'_i] = \bar{\mathbb{E}}[D_i D'_i] = Q$  is bounded away from zero and bounded from above in the matrix sense, uniformly in  $n$ . Moreover,  $\text{Var}(\mathbb{G}_n[D_i \epsilon_i]) = \Omega$  where  $\Omega = \sigma^2 \bar{\mathbb{E}}[D_i D'_i]$  under homoscedasticity and  $\Omega = \bar{\mathbb{E}}[\epsilon_i^2 D_i D'_i]$  under heteroscedasticity. In either case we have that  $\Omega$  is bounded away from zero and from above in the matrix sense, uniformly in  $n$ , by the assumptions the theorems. (Note that matrices  $\Omega$  and  $Q$  are implicitly indexed by  $n$ , but we omit the index to simplify notations.) Therefore,

$$\sqrt{n}(\hat{\alpha} - \alpha_0) = Q^{-1} \mathbb{G}_n[D_i \epsilon_i] + o_P(1),$$

and  $Z_n = (Q^{-1} \Omega Q^{-1})^{-1/2} \sqrt{n}(\hat{\alpha} - \alpha_0) = \mathbb{G}_n[z_{i,n}] + o_P(1)$ , where  $z_{i,n} = (Q^{-1} \Omega Q^{-1})^{-1/2} Q^{-1} D_i \epsilon_i$  are i.n.i.d. with mean zero and variance  $I$ . We have that for some small enough  $\delta > 0$   $\bar{\mathbb{E}}\|z_{i,n}\|_2^{2+\delta} \lesssim \bar{\mathbb{E}}\left[\|D_i\|_2^{2+\delta} |\epsilon_i|^{2+\delta}\right] \lesssim 1$ , by Condition SM. This condition verifies the Lyapunov condition, and the application of the Lyapunov CLT for i.n.i.d. triangular arrays and the Cramer-Wold device implies that  $Z_n \rightarrow_d N(0, I)$ .

Step 2. To show (F.32), note that

$$\begin{aligned}
\|\mathbb{E}_n[(\widehat{D}_i - D_i)d'_i]\| &\leq \mathbb{E}_n[\|\widehat{D}_i - D_i\|_2 \|d_i\|_2] \leq \sqrt{\mathbb{E}_n[\|\widehat{D}_i - D_i\|_2^2] \mathbb{E}_n[\|d_i\|_2^2]} \\
&= \sqrt{\mathbb{E}_n \left[ \sum_{l=1}^{k_e} |\widehat{D}_{il} - D_{il}|^2 \right] \mathbb{E}_n[\|d_i\|_2^2]} \leq \sqrt{k_e} \max_{1 \leq l \leq k_e} \|\widehat{D}_{il} - D_{il}\|_{2,n} \sqrt{\mathbb{E}_n[\|d_i\|_2^2]} \\
&\lesssim_P \max_{1 \leq l \leq k_e} \|\widehat{D}_{il} - D_{il}\|_{2,n} = o_P(1).
\end{aligned}$$

where  $\sqrt{\mathbb{E}_n[\|d_i\|_2^2]} \lesssim_P 1$  by  $\bar{\mathbb{E}}\|d_i\|_2^2 \lesssim 1$  and Chebyshev, and the last assertion holds by Step 0.

Moreover,  $\mathbb{E}_n[D_i D'_i] - \bar{\mathbb{E}}[D_i D'_i] \rightarrow_P 0$  by von Bahr-Essen inequality (von Bahr and Esseen, 1965) using that  $\bar{\mathbb{E}}[\|D_i\|_2^q]$  for a fixed  $q > 2$  is bounded uniformly in  $n$  by Condition SM.

Step 3. To show (F.33), let  $a_{il} := a_l(x_i)$ , note that  $\mathbb{E}[f_{ij}\epsilon_i] = 0$ ,  $\mathbb{E}[\epsilon_i|D_{il}] = 0$  and  $\mathbb{E}[\epsilon_{il}|a_{il}] = 0$ , and

$$\begin{aligned}
&\max_{1 \leq l \leq k_e} |\sqrt{n} \mathbb{E}_n[(\widehat{D}_{il} - D_{il})\epsilon_i]| \\
&= \max_{1 \leq l \leq k_e} |\sqrt{n} \mathbb{E}_n\{f'_i(\widehat{\beta}_l - \beta_{l0})\epsilon_i\} - \mathbb{G}_n\{a_{il}\epsilon_i\}| = \max_{1 \leq l \leq k_e} \left| \sum_{j=1}^p \mathbb{G}_n\{f_{ij}\epsilon_i\}'(\widehat{\beta}_{lj} - \beta_{l0j}) - \mathbb{G}_n\{a_{il}\epsilon_i\} \right| \\
&\leq \max_{1 \leq j \leq p} \left| \frac{\mathbb{G}_n[f_{ij}\epsilon_i]}{\sqrt{\mathbb{E}_n[f_{ij}^2\epsilon_i^2]}} \right| \max_{1 \leq j \leq p} \sqrt{\mathbb{E}_n[f_{ij}^2\epsilon_i^2]} \max_{1 \leq l \leq k_e} \|\widehat{\beta}_l - \beta_{l0}\|_1 + \max_{1 \leq l \leq k_e} |\mathbb{G}_n\{a_{il}\epsilon_i\}|.
\end{aligned}$$

Next we note that for each  $l = 1, \dots, k_e$   $|\mathbb{G}_n\{a_{il}\epsilon_i\}| \lesssim_P [\mathbb{E}_n a_{il}^2]^{1/2} \lesssim_P \sqrt{s/n} \rightarrow 0$ , by the Condition AS on  $[\mathbb{E}_n a_{il}^2]^{1/2}$  and by Chebyshev inequality, since in the homoscedastic case of Theorem 3:  $\text{Var}[\mathbb{G}_n\{a_{il}\epsilon_i\}|x_1, \dots, x_n] \leq \sigma^2 \mathbb{E}_n a_{il}^2$ , and in the bounded heteroscedastic case of Theorem 3:  $\text{Var}[\mathbb{G}_n\{a_{il}\epsilon_i\}|x_1, \dots, x_n] \lesssim \mathbb{E}_n a_{il}^2$ . Next we can bound  $\max_{1 \leq j \leq p} |\mathbb{G}_n[f_{ij}\epsilon_i]/\sqrt{\mathbb{E}_n[f_{ij}^2\epsilon_i^2]}| \lesssim_P \sqrt{\log p}$  provided that  $p$  obeys the growth condition  $\log p = o(n^{1/3})$ , and

$$\min_{1 \leq j \leq p} M_{j0} := \frac{\bar{\mathbb{E}}[f_{ij}^2\epsilon_i^2]^{1/2}}{\bar{\mathbb{E}}[|f_{ij}|^3|\epsilon_i|^3]^{1/3}} \gtrsim 1. \quad (\text{F.34})$$

This result follows by the bound on moderate deviations of a maximum of a self-normalized vector stated in Lemma 5, and by (F.34) holding by Condition SM. Finally,  $\max_{1 \leq j \leq p} \mathbb{E}_n[f_{ij}^2\epsilon_i^2] \lesssim_P 1$ , by Condition SM. Thus, combining bounds above with bounds in (F.30)-(F.31)

$$\max_{1 \leq l \leq k_e} |\sqrt{n} \mathbb{E}_n[(\widehat{D}_{il} - D_{il})\epsilon_i]| \lesssim_P \sqrt{\frac{s^2 \log^2(p \vee n)}{n}} + \sqrt{\frac{s}{n}} \rightarrow 0,$$

where the conclusion by Condition SM (iii).

Step 4. This step establishes consistency of the variance estimator in the homoscedastic case of Theorem 3.

Since  $\sigma^2$  and  $Q = \bar{\mathbb{E}}[D_i D'_i]$  are bounded away from zero and from above uniformly in  $n$ , it suffices to show  $\widehat{\sigma}^2 - \sigma^2 \rightarrow_P 0$  and  $\mathbb{E}_n[\widehat{D}_i \widehat{D}'_i] - \bar{\mathbb{E}}[D_i D'_i] \rightarrow_P 0$ . Indeed,  $\widehat{\sigma}^2 = \mathbb{E}_n[(\epsilon_i - d'_i(\widehat{\alpha} - \alpha_0))^2] =$

$\mathbb{E}_n[\epsilon_i^2] + 2\mathbb{E}_n[\epsilon_i d'_i(\alpha_0 - \hat{\alpha})] + \mathbb{E}_n[(d'_i(\alpha_0 - \hat{\alpha}))^2]$  so that  $\mathbb{E}_n[\epsilon_i^2] - \sigma^2 \rightarrow_P 0$  by Chebyshev inequality since  $\bar{\mathbb{E}}[|\epsilon_i|^4]$  is bounded uniformly in  $n$ , and the remaining terms converge to zero in probability since  $\hat{\alpha} - \alpha_0 \rightarrow_P 0$  by Step 3,  $\|\mathbb{E}_n[d_i \epsilon_i]\|_2 \lesssim_P 1$  by Markov and since  $\bar{\mathbb{E}}\|d_i \epsilon_i\|_2 \leq \sqrt{\bar{\mathbb{E}}\|d_i\|_2^2} \sqrt{\bar{\mathbb{E}}|\epsilon_i|^2}$  is uniformly bounded in  $n$  by Condition SM, and  $\mathbb{E}_n\|d_i\|_2^2 \lesssim_P 1$  by Markov and  $\bar{\mathbb{E}}\|d_i\|_2^2$  bounded uniformly in  $n$  by Condition SM. Next, note that

$$\|\mathbb{E}_n[\hat{D}_i \hat{D}'_i] - \mathbb{E}_n[D_i D'_i]\| = \|\mathbb{E}_n[D_i(\hat{D}_i - D_i)' + (\hat{D}_i - D_i)D'_i] + \mathbb{E}_n[(\hat{D}_i - D_i)(\hat{D}_i - D_i)']\|$$

which is bounded up to a constant by

$$\sqrt{k_e} \max_{1 \leq l \leq k_e} \|\hat{D}_{il} - D_{il}\|_{2,n} \|D_i\|_{2,n} + k_e \max_{1 \leq l \leq k_e} \|\hat{D}_{il} - D_{il}\|_{2,n}^2 \rightarrow_P 0$$

by (F.30) and by  $\|D_i\|_{2,n} \lesssim_P 1$  holding by Markov inequality. Moreover,  $\mathbb{E}_n[D_i D'_i] - \bar{\mathbb{E}}[D_i D'_i] \rightarrow_P 0$  by Step 2.

Step 5. This step establishes consistency of the variance estimator in the boundedly heteroscedastic case of Theorem 3.

Recall that  $\hat{\Omega} := \mathbb{E}_n[\hat{\epsilon}_i^2 \hat{D}(x_i) \hat{D}(x_i)']$  and  $\Omega := \bar{\mathbb{E}}[\epsilon_i^2 D(x_i) D(x_i)']$ , where the latter is bounded away from zero and from above uniformly in  $n$ . Also,  $Q = \bar{\mathbb{E}}[D_i D'_i]$  is bounded away from zero and from above uniformly in  $n$ . Therefore, it suffices to show  $\hat{\Omega} - \Omega \rightarrow_P 0$  and that  $\mathbb{E}_n[\hat{D}_i \hat{D}'_i] - \bar{\mathbb{E}}[D_i D'_i] \rightarrow_P 0$ . The latter has been shown in the previous step, and we only need to show the former.

In what follows, we shall repeatedly use the following elementary inequality: for arbitrary non-negative random variables  $W_1, \dots, W_n$  and  $q > 1$ :

$$\max_{i \leq n} W_i \lesssim n^{1/q} \text{ if } \bar{\mathbb{E}}[W_i^q] \lesssim 1, \quad (\text{F.35})$$

which follows by Markov inequality from  $\mathbb{E}[\max_{i \leq n} W_i] \leq n^{1/q} \mathbb{E}(\frac{1}{n} \sum_{i=1}^n W_i^q)^{1/q} \leq n^{1/q} (\bar{\mathbb{E}}[W_i^q])^{1/q}$ , which follows from the trivial bound  $\max_{i \leq n} |w_i| \leq \sum_{i=1}^n |w_i|$  and Jensen's inequality.

First, we note

$$\begin{aligned} \|\mathbb{E}_n[(\hat{\epsilon}_i^2 - \epsilon_i^2) \hat{D}_i \hat{D}'_i]\| &\leq \|\mathbb{E}_n[\{d'_i(\hat{\alpha} - \alpha_0)\}^2 \hat{D}_i \hat{D}'_i]\| + 2\|\mathbb{E}_n[\epsilon_i d'_i(\hat{\alpha} - \alpha_0) \hat{D}_i \hat{D}'_i]\| \\ &\lesssim_P \max_{i \leq n} \|d_i\|_2^2 n^{-1} \|\mathbb{E}_n[\hat{D}_i \hat{D}'_i]\| + \max_{i \leq n} |\epsilon_i| \|d_i\|_2 n^{-1/2} \|\mathbb{E}_n[\hat{D}_i \hat{D}'_i]\| \rightarrow_P 0, \end{aligned}$$

since  $\|\hat{\alpha} - \alpha_0\|_2^2 \lesssim_P 1/n$ ,  $\|\mathbb{E}_n \hat{D}_i \hat{D}'_i\| \lesssim_P 1$  by Step 4, and  $\max_{i \leq n} \|d_i\|_2^2 n^{-1} \rightarrow_P 0$  (by  $\max_{i \leq n} \|d_i\|_2 \lesssim_P n^{1/q}$  for  $q > 2$ , holding by  $\bar{\mathbb{E}}[\|d_i\|_2^q] \lesssim 1$  and inequality (F.35)) and  $\max_{i \leq n} [\|d_i\|_2 |\epsilon_i|] n^{-1/2} \rightarrow_P 0$  (by  $\max_{i \leq n} [\|d_i\|_2 |\epsilon_i|] \lesssim_P n^{1/q}$  for  $q > 2$  holding by  $\bar{\mathbb{E}}[(\|d_i\|_2 |\epsilon_i|)^2] \lesssim 1$  and inequality (F.35)).

Next we note that

$$\|\mathbb{E}_n[\epsilon_i^2 \hat{D}_i \hat{D}'_i] - \mathbb{E}_n[\epsilon_i^2 D_i D'_i]\| = \|\mathbb{E}_n[\epsilon_i^2 D_i(\hat{D}_i - D_i)' + \epsilon_i^2 (\hat{D}_i - D_i)D'_i] + \mathbb{E}_n[\epsilon_i^2 (\hat{D}_i - D_i)(\hat{D}_i - D_i)']\|$$

which is bounded up to a constant by

$$\sqrt{k_e} \max_{1 \leq l \leq k_e} \|\widehat{D}_{il} - D_{il}\|_{2,n} \|\epsilon_i^2\|_{2,n} \|D_i\|_2 + k_e \max_{1 \leq l \leq k_e} \|\widehat{D}_{il} - D_{il}\|_{2,n}^2 \max_{i \leq n} \epsilon_i^2 \rightarrow_P 0.$$

The latter occurs because  $\|\epsilon_i^2\|_{2,n} \|D_i\|_2 = \sqrt{\mathbb{E}_n[\epsilon_i^4 \|D_i\|_2^2]} \lesssim_P 1$  by  $\bar{\mathbb{E}}[\epsilon_i^4 \|D_i\|_2^2]$  uniformly bounded in  $n$  by Condition SM and by Markov inequality, and

$$\max_{1 \leq l \leq k_e} \|\widehat{D}_{il} - D_{il}\|_{2,n}^2 \max_{i \leq n} \epsilon_i^2 \lesssim_P \frac{s \log(p \vee n)}{n} n^{2/q_e} \rightarrow 0,$$

where the latter step holds by Step 0 and by  $\max_{i \leq n} \epsilon_i^2 \lesssim_P n^{2/q_e}$  holding by  $\bar{\mathbb{E}}[\epsilon_i^{q_e}] \lesssim 1$  and inequality (F.35). Finally,  $\mathbb{E}_n[\epsilon_i^2 D_i D_i'] - \bar{\mathbb{E}}[\epsilon_i^2 D_i D_i'] \rightarrow_P 0$  by the von Bahr-Essen inequality (von Bahr and Esseen, 1965) and by  $\bar{\mathbb{E}}[|\epsilon_i|^{2+\mu} \|D_i\|_2^{2+\mu}]$  bounded uniformly in  $n$  for small enough  $\mu > 0$  by Condition SM.

We conclude that  $\mathbb{E}_n[\widehat{\epsilon}_i^2 \widehat{D}_i \widehat{D}_i'] - \bar{\mathbb{E}}[\epsilon_i^2 D_i D_i'] \rightarrow_P 0$ .  $\square$

**F.2. Proof of Theorem 5.** Step 1. To establish claim (1), using the properties of projection we note that

$$n \mathbb{E}_n[\tilde{\epsilon}_i \tilde{f}_{ij}] = n \mathbb{E}_n[\epsilon_i \tilde{f}_{ij}]. \quad (\text{F.36})$$

Since for  $\widehat{\mu}_\epsilon = (\mathbb{E}_n[w_i w_i'])^{-1} \mathbb{E}_n[w_i \epsilon_i]$  we have  $\|\widehat{\mu}_\epsilon\|_2 \leq \|\mathbb{E}_n[w_i w_i']^{-1}\| \|\mathbb{E}_n[w_i \epsilon_i]\|_2$ , where  $\|\mathbb{E}_n[w_i w_i']^{-1}\|$  is bounded by SM2(ii) and  $\|\mathbb{E}_n[w_i \epsilon_i]\|_2$  is of stochastic order  $\sqrt{k_w/n}$  by Chebyshev inequality and SM2(ii). Hence  $\|\widehat{\mu}_\epsilon\|_2 \lesssim_P \sqrt{k_w/n}$ . Since  $\|w_i\|_2 \leq \zeta_w$  by Condition SM2(i), we conclude that  $\max_{i \leq n} |w_i' \widehat{\mu}_\epsilon| \lesssim_P \zeta_w \sqrt{k_w/n} \rightarrow 0$ . Hence, uniformly in  $j \in \{1, \dots, p\}$ ,

$$|\sqrt{\mathbb{E}_n[\tilde{\epsilon}_i^2 \tilde{f}_{ij}^2]} - \sqrt{\mathbb{E}_n[\epsilon_i^2 \tilde{f}_{ij}^2]}| \stackrel{(a)}{\leq} \sqrt{\mathbb{E}_n[(w_i' \widehat{\mu}_\epsilon)^2 \tilde{f}_{ij}^2]} \stackrel{(b)}{=} o_P(1) \sqrt{\mathbb{E}_n[\tilde{f}_{ij}^2]} \stackrel{(c)}{=} o_P(1), \quad (\text{F.37})$$

where (a) is by the triangular inequality and the decomposition  $\tilde{\epsilon}_i = \epsilon_i - w_i' \widehat{\mu}_\epsilon$ , (b) is by the Holder inequality, and (c) is by the normalization  $\sqrt{\mathbb{E}_n[\tilde{f}_{ij}^2]} = 1$  for each  $j$ . Hence, for  $c > 1$ , by (F.36) and (F.37)  $\text{wp} \rightarrow 1$

$$\Lambda_{\alpha_1} \leq c \bar{\Lambda}_{\alpha_1}, \quad \bar{\Lambda}_{\alpha_1} := \max_{1 \leq j \leq p} n |\mathbb{E}_n[\epsilon_i \tilde{f}_{ij}]| / \sqrt{\mathbb{E}_n[\epsilon_i^2 \tilde{f}_{ij}^2]}.$$

Since  $\bar{\Lambda}_{\alpha_1}$  is a maximum of self-normalized sum of i.n.i.d. terms conditional on  $X$ , application of SM2(iii)-(iv) and the moderate deviation bound from Lemma 5 for the self-normalized sum with  $U_{ij} = \epsilon_i \tilde{f}_{ij}$ , conditional on  $X$ , implies that  $P(c \bar{\Lambda}_{\alpha_1} \leq \Lambda(1 - \gamma)) \geq 1 - \gamma - o(1)$ . This verifies claim (i).

Step 2. To show claim (2) we note that using triangular and other elementary inequalities:

$$\Lambda_a = \max_{1 \leq j \leq p} \left| \frac{n |\mathbb{E}_n[(\tilde{\epsilon}_i - (a - \alpha_1)' \tilde{d}_{ei}) \tilde{f}_{ij}]|}{\sqrt{\mathbb{E}_n[(\tilde{\epsilon}_i - (a - \alpha_1)' \tilde{d}_{ei})^2 \tilde{f}_{ij}^2]}} \right| \geq \max_{1 \leq j \leq p} \left| \frac{n |\mathbb{E}_n[(a - \alpha_1)' \tilde{d}_{ei} \tilde{f}_{ij}]|}{\sqrt{\mathbb{E}_n[\tilde{\epsilon}_i^2 \tilde{f}_{ij}^2]} + \sqrt{\mathbb{E}_n[\{(a - \alpha_1)' \tilde{d}_{ei}\}^2 \tilde{f}_{ij}^2]}} \right| - \Lambda_{\alpha_1}.$$

The first term on the right side is bounded below by,  $\text{wp} \rightarrow 1$ ,

$$\max_{1 \leq j \leq p} \frac{n|\mathbb{E}_n[(a - \alpha_1)' \tilde{d}_{ei} \tilde{f}_{ij}]|}{c \sqrt{\mathbb{E}_n[\epsilon_i^2 \tilde{f}_{ij}^2]} + \sqrt{\mathbb{E}_n[\{(a - \alpha_1)' \tilde{d}_{ei}\}^2 \tilde{f}_{ij}^2]}},$$

by Step 1 for some  $c > 1$ , and  $\Lambda_{\alpha_1} \lesssim_P \sqrt{n \log(p/\gamma)}$  also by Step 1. Hence for any constant  $C$ , by the last condition in the statement of the theorem, with probability converging to 1,  $\Lambda_a - C\sqrt{n \log(p/\gamma)} \rightarrow +\infty$ , so that Claim (2) immediately follows, since  $\Lambda(1 - \gamma) \lesssim \sqrt{n \log(p/\gamma)}$ .  $\square$

**F.3. Proof of Theorems 6 and 7.** See Online Appendix.

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Table 1. Simulation Results.

Estimator	Exponential				S = 5				S = 50			
	N(0)	Median Bias	MAD	rp(.05)	N(0)	Median Bias	MAD	rp(.05)	N(0)	Median Bias	MAD	rp(.05)
A. Concentration Parameter = 30, n = 100												
2SLS(100)		0.524	0.524	1.000		0.520	0.520	1.000		0.528	0.528	0.998
FULL(100)		0.373	0.741	0.646		0.476	0.781	0.690		0.285	0.832	0.580
Post-LASSO	483	0.117	0.183	0.012	485	0.128	0.178	0.008	498	0.363	0.368	0.012
Post-LASSO-F	483	0.117	0.184	0.012	485	0.128	0.178	0.008	498	0.363	0.368	0.012
Post-LASSO (Ridge)	500	0.229	0.263	0.000	500	0.212	0.239	0.000	500	0.362	0.364	0.002
Post-LASSO-F (Ridge)	500	0.229	0.263	0.000	500	0.212	0.239	0.000	500	0.362	0.364	0.002
sup-Score				0.006				0.000				0.008
B. Concentration Parameter = 30, n = 250												
2SLS(100)		0.493	0.493	1.000		0.485	0.485	1.000		0.486	0.486	1.000
FULL(100)		0.028	0.286	0.076		0.023	0.272	0.056		0.046	0.252	0.072
Post-LASSO	396	0.106	0.163	0.044	423	0.105	0.165	0.042	499	0.358	0.359	0.008
Post-LASSO-F	396	0.107	0.164	0.048	423	0.105	0.166	0.044	499	0.358	0.359	0.008
Post-LASSO (Ridge)	500	0.191	0.223	0.004	500	0.196	0.217	0.006	500	0.353	0.355	0.000
Post-LASSO-F (Ridge)	500	0.191	0.223	0.004	500	0.196	0.217	0.006	500	0.353	0.355	0.000
sup-Score				0.002				0.010				0.006
C. Concentration Parameter = 180, n = 100												
2SLS(100)		0.353	0.353	0.952		0.354	0.354	0.958		0.350	0.350	0.948
FULL(100)		0.063	0.563	0.648		0.096	0.562	0.694		0.148	0.538	0.656
Post-LASSO	120	0.037	0.093	0.078	132	0.035	0.100	0.052	498	0.192	0.211	0.000
Post-LASSO-F	120	0.030	0.093	0.070	132	0.025	0.100	0.046	498	0.192	0.211	0.000
Post-LASSO (Ridge)	500	0.061	0.132	0.002	500	0.063	0.116	0.000	500	0.004	0.119	0.000
Post-LASSO-F (Ridge)	500	0.061	0.132	0.002	500	0.063	0.116	0.000	500	0.004	0.119	0.000
sup-Score				0.002				0.002				0.000
D. Concentration Parameter = 180, n = 250												
2SLS(100)		0.289	0.289	0.966		0.281	0.281	0.972		0.280	0.280	0.964
FULL(100)		0.008	0.082	0.058		0.007	0.081	0.044		0.008	0.083	0.048
Post-LASSO	0	0.032	0.073	0.054	0	0.019	0.067	0.060	411	0.233	0.237	0.044
Post-LASSO-F	0	0.024	0.069	0.038	0	0.014	0.068	0.046	411	0.235	0.236	0.040
Post-LASSO (Ridge)	211	0.062	0.095	0.098	225	0.058	0.084	0.082	295	-0.008	0.090	0.030
Post-LASSO-F (Ridge)	211	0.061	0.096	0.082	225	0.056	0.081	0.062	295	-0.004	0.090	0.032
sup-Score				0.012				0.012				0.012

Note: Results are based on 500 simulation replications and 100 instruments. Column labels indicate the structure of the first-stage coefficients as described in the text. 2SLS(100) and FULL(100) are respectively the 2SLS and Fuller(1) estimators using all 100 potential instruments. Post-LASSO and Post-LASSO-F respectively correspond to 2SLS and Fuller(1) using the instruments selected from LASSO variable selection among the 100 instruments with inference based on the asymptotic normal approximation; in cases where no instruments are selected, the procedure switches to using the sup-Score test for inference. sup-Score provides the rejection frequency for a weak identification robust procedure that is suited to situations with more instruments than observations. Post-LASSO (Ridge) and Post-LASSO-F (Ridge) are defined as Post-LASSO and Post-LASSO-F but augment the instrument set with a fitted value obtained via ridge regression as described in the text. We report the number of replications in which LASSO selected no instruments (N(0)), median bias (Med. Bias), median absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). In cases where LASSO selects no instruments, Med. Bias, and MAD are based on 2SLS using the single instrument with the largest sample correlation to the endogenous variable and rp(.05) is based on the sup-Score test.

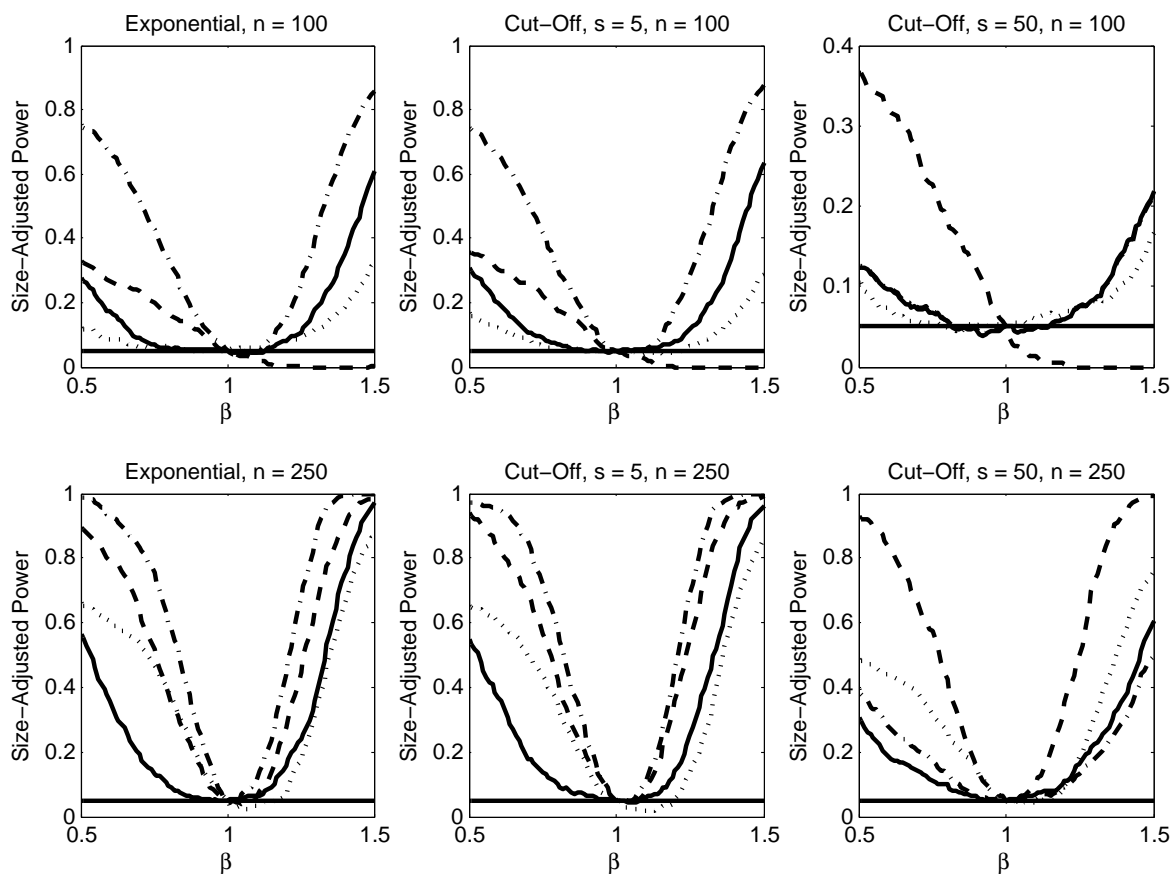


FIGURE 1. Size-adjusted power curves for Post-Lasso-F (dot-dash), Post-Lasso-F (Ridge) (dotted), FULL(100) (dashed), and sup-Score (solid) from the simulation example with concentration parameter of 180 for  $n = 100$  and  $n = 250$ .

Table 2: Effect of Federal Appellate Takings Law Decisions on Economic Outcomes

	Home Prices			GDP
	log(FHFA)	log(Non-Metro)	log(Case-Shiller)	log(GDP)
Sample Size	312	110	183	312
OLS	0.0114	0.0108	0.0152	0.0099
s.e.	0.0132	0.0066	0.0132	0.0048
2SLS	0.0262	0.0480	0.0604	0.0165
s.e.	0.0441	0.0212	0.0296	0.0162
FS-W	28.0859	82.9647	67.7452	28.0859
Post-LASSO	0.0369	0.0357	0.0631	0.0133
s.e.	0.0465	0.0132	0.0249	0.0161
FS-W	44.5337	243.1946	89.5950	44.5337
S	1	4	2	1
Post-LASSO+	0.0314	0.0348	0.0628	0.0144
s.e.	0.0366	0.0127	0.0245	0.0131
FS-W	73.3010	260.9823	105.3206	73.3010
S	3	6	3	3
Spec. Test	-0.2064	0.5753	-0.0985	0.1754

Note: This table reports the estimated effect of an additional pro-plaintiff takings decision, a decision that goes against the government and leaves the property in the hands of the private owner, on various economic outcomes using two-stage least squares (2SLS). The characteristics of randomly assigned judges serving on the panel that decides the case are used as instruments for the decision variable. All estimates include circuit effects, circuit-specific time trends, time effects, controls for the number of cases in each circuit-year, and controls for the demographics of judges available within each circuit-year. Each column corresponds to a different dependent variable. log(FHFA), log(Non-Metro), and log(Case-Shiller) are within-circuit averages of log-house-price-indexes, and log(GDP) is the within-circuit average of log of state-level GDP. OLS are ordinary least squares estimates. 2SLS is the 2SLS estimator with the original instruments in Chen and Yeh (2010). Post-LASSO provides 2SLS estimates obtained using instruments selected by LASSO with the refined data-dependent penalty choice. Post-LASSO+ uses the union of the instruments selected by Lasso and the instruments of Chen and Yeh (2010). Rows labeled s.e. provide the estimated standard errors of the associated estimator. All standard errors are computed with clustering at the circuit-year level. FS-W is the value of the first-stage Wald statistic using the selected instrument. S is the number of instruments used in obtaining the 2SLS estimates. Hausman test is the value of a Hausman test statistic comparing the 2SLS estimate of the effect of takings law decisions using the Chen and Yeh (2010) instruments to the estimated effect using the LASSO-selected instruments.

# Online Appendix for “Sparse Models and Methods for Optimal Instruments with an Application to Eminent Domain”

## APPENDIX A. TOOLS

### A.1. Lyapunov CLT, Rosenthal Inequality, and Von Bahr-Esseen Inequality.

**Lemma 1** (Lyapunov CLT). *Let  $\{X_{i,n}, i = 1, \dots, n\}$  be independent zero-mean random variables with variance  $s_{i,n}^2$ ,  $n = 1, 2, \dots$ . Define  $s_n^2 = \sum_{i=1}^n s_{i,n}^2$ . If for some  $\mu > 0$ , the Lyapunov's condition holds:*

$$\lim_{n \rightarrow \infty} \frac{1}{s_n^{2+\mu}} \sum_{i=1}^n \mathbb{E} [|X_{i,n}|^{2+\mu}] = 0$$

*then as  $n$  goes to infinity:*

$$\frac{1}{s_n} \sum_{i=1}^n X_{i,n} \rightarrow_d \mathcal{N}(0, 1).$$

**Lemma 2** (Rosenthal Inequality). *Let  $X_1, \dots, X_n$  be independent zero-mean random variables, then for  $r \geq 2$*

$$\mathbb{E} \left( \left| \sum_{i=1}^n X_i \right|^r \right) \leq C(r) \max \left[ \sum_{i=1}^n \mathbb{E}(|X_i|^r), \left\{ \sum_{i=1}^n \mathbb{E}(X_i^2) \right\}^{r/2} \right].$$

This is due to Rosenthal (1970).

**Corollary 1.** *Let  $r \geq 2$ , and consider the case of independent zero-mean variables  $X_i$  with  $\mathbb{E} \mathbb{E}_n(X_i^2) = 1$  and  $\mathbb{E} \mathbb{E}_n(|X_i|^r)$  bounded by  $C$ . Then for any  $\ell_n \rightarrow \infty$*

$$Pr \left( \frac{|\sum_{i=1}^n X_i|}{n} > \ell_n n^{-1/2} \right) \leq \frac{2C(r)C}{\ell_n^r} \rightarrow 0.$$

To verify the corollary, we use Rosenthal's inequality  $\mathbb{E}(|\sum_{i=1}^n X_i|^r) \leq C n^{r/2}$ , and the result follows by Markov inequality,

$$P \left( \frac{|\sum_{i=1}^n X_i|}{n} > c \right) \leq \frac{C(r)C n^{r/2}}{c^r n^r} \leq \frac{C(r)C}{c^r n^{r/2}}.$$

**Lemma 3** (von Bahr-Essen Inequality). *Let  $X_1, \dots, X_n$  be independent zero-mean random variables. Then for  $1 \leq r \leq 2$*

$$\mathbb{E} \left( \left| \sum_{i=1}^n X_i \right|^r \right) \leq (2 - n^{-1}) \cdot \sum_{k=1}^n \mathbb{E}(|X_k|^r).$$

This result is due to von Bahr and Esseen (1965).

**Corollary 2.** *Let  $r \in [1, 2]$ , and consider the case of independent zero-mean variables  $X_i$  with  $\mathbb{E}\mathbb{E}_n(|X_i|^r)$  bounded by  $C$ . Then for any  $\ell_n \rightarrow \infty$*

$$\mathbb{P} \left\{ \frac{|\sum_{i=1}^n X_i|}{n} > \ell_n n^{-(1-1/r)} \right\} \leq \frac{2C}{\ell_n^r} \rightarrow 0.$$

The corollary follow by Markov and von Bahr-Esseen's inequalities,

$$\mathbb{P} \left( \frac{|\sum_{i=1}^n X_i|}{n} > c \right) \leq \frac{CE(|\sum_{i=1}^n X_i|^r)}{c^r n^r} \leq \frac{\sum_{i=1}^n \mathbb{E}(|X_i|^r)}{c^r n^r} \leq C \frac{\bar{\mathbb{E}}(|X_i|^r)}{c^r n^{r-1}}.$$

**A.2. A Symmetrization-based Probability Inequality.** Next we proceed to use symmetrization arguments to bound the empirical process. Let  $\|f\|_{\mathbb{P}_{n,2}} = \sqrt{\mathbb{E}_n[f(Z_i)^2]}$ ,  $\mathbb{G}_n(f) = \sqrt{n}\mathbb{E}_n[f(Z_i) - \mathbb{E}[Z_i]]$ , and for a random variable  $Z$  let  $q(Z, 1 - \tau)$  denote its  $(1 - \tau)$ -quantile. The proof follows standard symmetrization arguments.

**Lemma 4** (Maximal inequality via symmetrization). *Let  $Z_1, \dots, Z_n$  be arbitrary independent stochastic processes and  $\mathcal{F}$  a finite set of measurable functions. For any  $\tau \in (0, 1/2)$ , and  $\delta \in (0, 1)$  with probability at least  $1 - 4\tau - 4\delta$  we have*

$$\sup_{f \in \mathcal{F}} |\mathbb{G}_n(f)| \leq 4\sqrt{2 \log(2|\mathcal{F}|/\delta)} q(\sup_{f \in \mathcal{F}} \|f\|_{\mathbb{P}_{n,2}}, 1 - \tau) \vee 2 \sup_{f \in \mathcal{F}} q(|\mathbb{G}_n(f)|, 1/2).$$

*Proof.* Let

$$e_{1n} = \sqrt{2 \log(2|\mathcal{F}|/\delta)} q \left( \max_{f \in \mathcal{F}} \sqrt{\mathbb{E}_n[f(Z_i)^2]}, 1 - \tau \right), \quad e_{2n} = \max_{f \in \mathcal{F}} q \left( |\mathbb{G}_n(f(Z_i))|, \frac{1}{2} \right)$$

and the event  $\mathcal{E} = \{\max_{f \in \mathcal{F}} \sqrt{\mathbb{E}_n[f^2(Z_i)]} \leq q(\max_{f \in \mathcal{F}} \sqrt{\mathbb{E}_n[f^2(Z_i)]}, 1 - \tau)\}$  which satisfies  $P(\mathcal{E}) \geq 1 - \tau$ . By the symmetrization Lemma 2.3.7 of van der Vaart and Wellner (1996) (by definition of  $e_{2n}$  we have  $\beta_n(x) \geq 1/2$  in Lemma 2.3.7) we obtain

$$\begin{aligned} \mathbb{P} \{ \max_{f \in \mathcal{F}} |\mathbb{G}_n(f(Z_i))| > 4e_{1n} \vee 2e_{2n} \} &\leq 4\mathbb{P} \{ \max_{f \in \mathcal{F}} |\mathbb{G}_n(\varepsilon_i f(Z_i))| > e_{1n} \} \\ &\leq 4\mathbb{P} \{ \max_{f \in \mathcal{F}} |\mathbb{G}_n(\varepsilon_i f(Z_i))| > e_{1n} | \mathcal{E} \} + 4\tau \end{aligned}$$

where  $\varepsilon_i$  are independent Rademacher random variables,  $P(\varepsilon_i = 1) = P(\varepsilon_i = -1) = 1/2$ .

Thus a union bound yields

$$\mathbb{P} \left\{ \max_{f \in \mathcal{F}} |\mathbb{G}_n(f(Z_i))| > 4e_{1n} \vee 2e_{2n} \right\} \leq 4\tau + 4|\mathcal{F}| \max_{f \in \mathcal{F}} \mathbb{P} \{ |\mathbb{G}_n(\varepsilon_i f(Z_i))| > e_{1n} | \mathcal{E} \}. \quad (\text{A.38})$$

We then condition on the values of  $Z_1, \dots, Z_n$  and  $\mathcal{E}$ , denoting the conditional probability measure as  $\mathbb{P}_\varepsilon$ . Conditional on  $Z_1, \dots, Z_n$ , by the Hoeffding inequality the symmetrized process  $\mathbb{G}_n(\varepsilon_i f(Z_i))$  is sub-Gaussian for the  $L_2(\mathbb{P}_n)$  norm, namely, for  $f \in \mathcal{F}$ ,  $\mathbb{P}_\varepsilon \{ |\mathbb{G}_n(\varepsilon_i f(Z_i))| > x \} \leq 2 \exp(-x^2 / \{2\mathbb{E}_n[f^2(Z_i)]\})$ . Hence, under the event  $\mathcal{E}$ , we can bound

$$\mathbb{P}_\varepsilon \{ |\mathbb{G}_n(\varepsilon_i f(Z_i))| > e_{1n} | Z_1, \dots, Z_n, \mathcal{E} \} \leq 2 \exp(-e_{1n}^2 / [2\mathbb{E}_n[f^2(Z_i)]]) \leq 2 \exp(-\log(2|\mathcal{F}|/\delta)).$$

Taking the expectation over  $Z_1, \dots, Z_n$  does not affect the right hand side bound. Plugging in this bound yields the result.  $\square$

## APPENDIX B. PROOF OF THEOREM 6.

*Proof of Theorem 6.* To show part 1, note that by a standard argument

$$\sqrt{n}(\tilde{\alpha} - \alpha) = M^{-1}\mathbb{G}_n[A_i\epsilon_i] + o_P(1).$$

From the proof of Theorem 4 we have that

$$\sqrt{n}(\hat{\alpha} - \alpha_a) = Q^{-1}\mathbb{G}_n[D(x_i)\epsilon_i] + o_P(1).$$

The conclusion follows. The consistency of  $\hat{\Sigma}$  for  $\Sigma$  can be demonstrated similarly to the proof of consistency of  $\hat{\Omega}$  and  $\hat{Q}$  in the proof of Theorem 4.

To show part 2, let  $\alpha$  denote the true value as before, which by assumption coincides with the estimand of the baseline IV estimator by the standard argument,  $\tilde{\alpha} - \alpha = o_P(1)$ . The baseline IV estimator is consistent for this quantity. Under the alternative hypothesis, the estimand of  $\hat{\alpha}$  is

$$\alpha_a = \bar{\mathbb{E}}[D(x_i)d'_i]^{-1}\bar{\mathbb{E}}[D(x_i)y_i] = \alpha + \bar{\mathbb{E}}[D(x_i)D(x_i)']^{-1}\bar{\mathbb{E}}[D(x_i)\epsilon_i].$$

Under the alternative hypothesis,  $\|\bar{\mathbb{E}}[D(x_i)\epsilon_i]\|_2$  is bounded away from zero uniformly in  $n$ . Hence, since the eigenvalues of  $Q$  are bounded away from zero uniformly in  $n$ ,  $\|\alpha - \alpha_a\|_2$  is also bounded away from zero uniformly in  $n$ . Thus, it remains to show that  $\hat{\alpha}$  is consistent for  $\alpha_a$ . We have that

$$\hat{\alpha} - \alpha_a = \mathbb{E}_n[\hat{D}(x_i)d'_i]^{-1}\mathbb{E}_n[\hat{D}(x_i)\epsilon_i] - \bar{\mathbb{E}}[D(x_i)D(x_i)']^{-1}\bar{\mathbb{E}}[D(x_i)\epsilon_i]$$

so that

$$\|\hat{\alpha} - \alpha_a\|_2 \leq \|\mathbb{E}_n[\hat{D}(x_i)d'_i]^{-1} - \bar{\mathbb{E}}[D(x_i)D(x_i)']^{-1}\| \|\mathbb{E}_n[\hat{D}(x_i)\epsilon_i]\|_2 + \quad (\text{B.39})$$

$$+ \|\bar{\mathbb{E}}[D(x_i)D(x_i)]^{-1}\| \|\mathbb{E}_n[\hat{D}(x_i)\epsilon_i] - \bar{\mathbb{E}}[D(x_i)\epsilon_i]\|_2 = o_P(1), \quad (\text{B.40})$$

provided that (i)  $\|\mathbb{E}_n[\hat{D}(x_i)d'_i]^{-1} - \bar{\mathbb{E}}[D(x_i)D(x_i)']^{-1}\| = o_P(1)$ , which is shown in the proof of Theorem 4; (ii)  $\|\bar{\mathbb{E}}[D(x_i)D(x_i)]^{-1}\| = \|Q^{-1}\|$  is bounded from above uniformly in  $n$ , which follows from the assumption on  $Q$  in Theorem 4; and (iii)

$$\|\mathbb{E}_n[\hat{D}(x_i)\epsilon_i] - \bar{\mathbb{E}}[D(x_i)\epsilon_i]\|_2 = o_P(1), \quad \|\bar{\mathbb{E}}[D(x_i)\epsilon_i]\|_2 = O(1),$$

where  $\|\bar{\mathbb{E}}[D(x_i)\epsilon_i]\|_2 = O(1)$  is assumed. To show the last claim note that

$$\begin{aligned} \|\mathbb{E}_n[\hat{D}(x_i)\epsilon_i] - \bar{\mathbb{E}}[D(x_i)\epsilon_i]\|_2 &\leq \|\mathbb{E}_n[\hat{D}(x_i)\epsilon_i] - \mathbb{E}_n[D(x_i)\epsilon_i]\|_2 + \|\mathbb{E}_n[D(x_i)\epsilon_i] - \bar{\mathbb{E}}[D(x_i)\epsilon_i]\|_2 \\ &\leq \sqrt{k_e} \max_{1 \leq l \leq k_e} \|D_l(x_i) - \hat{D}_l(x_i)\|_{2,n} \|\epsilon_i\|_{2,n} + o_P(1) = o_P(1), \end{aligned}$$

since  $k_e$  is fixed,  $\|\mathbb{E}_n[D(x_i)\epsilon_i] - \bar{\mathbb{E}}[D(x_i)\epsilon_i]\|_2 = o_P(1)$  by von Bahr-Essen inequality von Bahr and Esseen (1965) and SM,  $\|\epsilon_i\|_{2,n} = O_P(1)$  follows by the Markov inequality and assumptions on the moments of  $\epsilon_i$ , and  $\max_{1 \leq l \leq k_e} \|D_l(x_i) - \hat{D}_l(x_i)\|_{2,n} = o_P(1)$  follows from Theorems 1 and 2.  $\square$



## APPENDIX C. PROOF OF THEOREM 7

We introduce additional superscripts  $a$  and  $b$  on all variables; and  $n$  gets replaced by either  $n_a$  or  $n_b$ . The proof is divided in steps. Assuming

$$\max_{1 \leq l \leq k_e} \|\widehat{D}_{il}^k - D_{il}^k\|_{2, n_k} \lesssim_P \sqrt{\frac{s \log(p \vee n)}{n}} = o_P(1), \quad k = a, b, \quad (\text{C.41})$$

Steps 1 establishes bounds for the intermediary estimates on each subsample. Step 2 establishes the result for the final estimator  $\widehat{\alpha}_{ab}$  and consistency of the matrices estimates. Finally, Step 3 establishes (C.41).

Step 1. We have that

$$\begin{aligned} \sqrt{n_k}(\widehat{\alpha}_k - \alpha_0) &= \mathbb{E}_{n_k}[\widehat{D}_i^k d_i^{k'}]^{-1} \sqrt{n} \mathbb{E}_{n_k}[\widehat{D}_i^k \epsilon_i^k] \\ &= \{\mathbb{E}_{n_k}[\widehat{D}_i^k d_i^{k'}]\}^{-1} \left( \mathbb{G}_{n_k}[D_i^k \epsilon_i^k] + o_P(1) \right) \\ &= \{\mathbb{E}_{n_k}[D_i D_i'] + o_P(1)\}^{-1} \left( \mathbb{G}_{n_k}[D_i^k \epsilon_i^k] + o_P(1) \right) \end{aligned}$$

since

$$\mathbb{E}_{n_k}[\widehat{D}_i^k d_i^{k'}] = \mathbb{E}_{n_k}[D_i D_i'] + o_P(1) \quad (\text{C.42})$$

$$\sqrt{n} \mathbb{E}_{n_k}[\widehat{D}_i^k \epsilon_i^k] = \mathbb{G}_{n_k}[D_i^k \epsilon_i^k] + o_P(1). \quad (\text{C.43})$$

Indeed, (C.42) follows similarly to Step 2 in the proof of Theorems 4 and 5 and condition (C.41). The relation (C.43) follows from  $\mathbb{E}[\epsilon_i^k | x_i^k] = 0$  for both  $k = a$  and  $k = b$ , Chebyshev inequality and

$$E[\|\sqrt{n} \mathbb{E}_{n_k}[(\widehat{D}_i^k - D_{il}^k) \epsilon_i^k]\|_2^2 | x_i^k, i = 1, \dots, n, k^c] \lesssim \sqrt{k_e} \max_{1 \leq l \leq k_e} \|(\widehat{D}_{il}^k - D_{il}^k)\|_{2, n_k}^2 \rightarrow_P 0,$$

where  $E[\cdot | x_i^k, i = 1, \dots, n, k^c]$  denotes the estimate computed conditional  $x_i^k, i = 1, \dots, n$  and on the sample  $k^c$ , where  $k^c = \{a, b\} \setminus k$ . The bound follows from the fact that (a)

$$\widehat{D}_{il}^k - D_{il}^k = f(x_i^k)'(\widehat{\beta}_l^{k^c} - \beta_{0l}^{k^c}) - a_l(x_i^k), 1 \leq i \leq n_k,$$

by Condition AS, where  $(\widehat{\beta}_l^{k^c} - \beta_{0l}^{k^c})$  are independent of  $\{\epsilon_i^k, 1 \leq i \leq n_k\}$ , by the independence of the two subsamples  $k$  and  $k^c$ , (b)  $\{\epsilon_i^k, x_i, 1 \leq i \leq n_k\}$  are independent across  $i$  and independent from the sample  $k^c$ , (c)  $\{\epsilon_i^k, 1 \leq i \leq n_k\}$  have conditional mean equal to zero, conditional on  $x_i^k, i = 1, \dots, n$  and have conditional variance bounded from above, uniformly in  $n$ , conditional on  $x_i^k, i = 1, \dots, n$ , by Condition SM, and (d) that  $\max_{1 \leq l \leq k_e} \|\widehat{D}_{il}^k - D_{il}^k\|_{2, n_k} \rightarrow_P 0$ .

Using the same arguments as in Step 1 in the proof of Theorems 4 and 5,

$$\sqrt{n_k}(\widehat{\alpha}_k - \alpha_0) = (\mathbb{E}_{n_k}[D_i^k D_i^{k'}])^{-1} \mathbb{G}_{n_k}[D_i^k \epsilon_i^k] + o_P(1) = O_P(1).$$

Step 2. Now putting together terms we get

$$\begin{aligned}
\sqrt{n}(\hat{\alpha}_{ab} - \alpha_0) &= ((n_a/n)\mathbb{E}_{n_a}[\hat{D}_i^a \hat{D}_i^{a'}] + (n_b/n)\mathbb{E}_{n_b}[\hat{D}_i^b \hat{D}_i^{b'}])^{-1} \times \\
&\times ((n_a/n)\mathbb{E}_{n_a}[\hat{D}_i^a \hat{D}_i^{a'}]\sqrt{n}(\hat{\alpha}_a - \alpha_0) + (n_b/n)\mathbb{E}_{n_b}[\hat{D}_i^b \hat{D}_i^{b'}]\sqrt{n}(\hat{\alpha}_b - \alpha_0)) \\
&= ((n_a/n)\mathbb{E}_{n_a}[D_i^a D_i^{a'}] + (n_b/n)\mathbb{E}_{n_b}[D_i^b D_i^{b'}])^{-1} \times \\
&\times ((n_a/n)\mathbb{E}_{n_a}[D_i^a D_i^{a'}]\sqrt{n}(\hat{\alpha}_a - \alpha_0) + (n_b/n)\mathbb{E}_{n_b}[D_i^b D_i^{b'}]\sqrt{n}(\hat{\alpha}_b - \alpha_0)) + o_P(1) \\
&= \{\mathbb{E}_n[D_i D_i']\}^{-1} \times \{(1/\sqrt{2}) \times \mathbb{G}_{n_a}[D_i^a \epsilon_i] + (1/\sqrt{2})\mathbb{G}_{n_b}[D_i^b \epsilon_i]\} + o_P(1) \\
&= \{\mathbb{E}_n[D_i D_i']\}^{-1} \times \mathbb{G}_n[D_i \epsilon_i] + o_P(1)
\end{aligned}$$

where we are also using the fact that

$$\mathbb{E}_{n_k}[\hat{D}_i^k \hat{D}_i^{k'}] - \mathbb{E}_{n_k}[D_i^k D_i^{k'}] = o_P(1),$$

which is shown similarly to the proofs given in Theorem 4 for showing that  $\mathbb{E}_n[D_i D_i'] - \mathbb{E}_n[D_i D_i'] = o_P(1)$ . The conclusion of the theorem follows by an application of Liapunov CLT, similarly to the proof in of Theorem 4 of the main text.

Step 3. In this step we establish (C.41). For every observation  $i$  and  $l = 1, \dots, k_e$ , by Condition AS we have

$$D_{il} = f_i' \beta_{l0} + a_l(x_i), \quad \|\beta_{l0}\|_0 \leq s, \quad \max_{1 \leq l \leq k_e} \|a_l(x_i)\|_{2,n} \leq c_s \lesssim_P \sqrt{s/n}. \quad (\text{C.44})$$

Under our conditions, the sparsity bound for LASSO by Lemma 9 implies that for all  $\delta_l^k = \hat{\beta}_l^k - \beta_{l0}$ ,  $k = a, b$ , and  $l = 1, \dots, k_e$

$$\|\delta_l^k\|_0 \lesssim_P s.$$

Therefore, by condition SE, we have for  $M = \mathbb{E}_{n_k}[f_i^k f_i^{k'}]$ ,  $k = a, b$ , that with probability going to 1, for  $n$  large enough

$$0 < \kappa' \leq \phi_{\min}(\|\delta_l^k\|_0)(M) \leq \phi_{\max}(\|\delta_l^k\|_0)(M) \leq \kappa'' < \infty,$$

where  $\kappa'$  and  $\kappa''$  are some constants that do not depend on  $n$ . Thus,

$$\begin{aligned}
\|D_{il}^k - \hat{D}_{il}^k\|_{2,n_k} &= \|f_i^{k'} \beta_{l0} + a_l(x_i^k) - f_i^{k'} \hat{\beta}_l^{k,c}\|_{2,n_k} \\
&= \|f_i^{k'}(\beta_{l0} - \hat{\beta}_l^{k,c})\|_{2,n_k} + \|a_l(x_i^k)\|_{2,n_k} \\
&\leq \sqrt{\kappa''/\kappa'} \|f_i^{k,c'}(\hat{\beta}_l^{k,c} - \beta_{l0})\|_{2,n_{k,c}} + c_s \sqrt{n/n_k}
\end{aligned} \quad (\text{C.45})$$

where the last inequality holds with probability going to 1 by Condition SE imposed on matrices  $M = \mathbb{E}_{n_k}[f_i^k f_i^{k'}]$ ,  $k = a, b$ , and by

$$\|a_l(x_i^k)\|_{2,n_k} \leq \sqrt{n/n_k} \|a_l(x_i)\|_{2,n} \leq \sqrt{n/n_k} c_s.$$

Then, in view of (C.44),  $\sqrt{n/n_k} = \sqrt{2} + o(1)$ , and condition  $s \log p = o(n)$ , the result (C.41) holds by (C.45) combined with Theorem 1 for LASSO and Theorem 2 for Post-LASSO which

imply

$$\max_{1 \leq l \leq k_e} \|f_i^{k'}(\hat{\beta}_l^k - \beta_{l0})\|_{2, n_k} \lesssim_P \sqrt{\frac{s \log(p \vee n)}{n}} = o_P(1), \quad k = a, b.$$

□

#### APPENDIX D. PROOF OF LEMMA 3.

Part 1. The first condition in RF(iv) is assumed, and we omit the proof for the third condition since it is analogous to the proof for the second condition.

Note that  $\max_{1 \leq j \leq p} \mathbb{E}_n[f_{ij}^4 v_{il}^4] \leq (\mathbb{E}_n[v_{il}^8])^{1/2} \max_{1 \leq j \leq p} (\mathbb{E}_n[f_{ij}^8])^{1/2} \lesssim_P 1$  since  $\max_{1 \leq j \leq p} \sqrt{\mathbb{E}_n[f_{ij}^8]} \lesssim_P 1$  by assumption and  $\max_{1 \leq l \leq k_e} \sqrt{\mathbb{E}_n[v_{il}^8]} \lesssim_P 1$  by the bounded  $k_e$ , Markov inequality, and the assumption that  $\bar{\mathbb{E}}[v_{il}^8]$  are uniformly bounded in  $n$  and  $l$ .

Thus, applying Lemma 4,

$$\max_{1 \leq l \leq k_e, 1 \leq j \leq p} |\mathbb{E}_n[f_{ij}^2 v_{il}^2] - \bar{\mathbb{E}}[f_{ij}^2 v_{il}^2]| \lesssim_P \sqrt{\frac{\log(pk_e)}{n}} \lesssim_P \sqrt{\frac{\log p}{n}} \rightarrow_P 0.$$

Part 2. To show (1), we note that by simple union bounds and tail properties of Gaussian variable, we have that  $\max_{ij} f_{ij}^2 \lesssim_P \log(p \vee n)$ , so we need  $\log(p \vee n) \frac{s \log(p \vee n)}{n} \rightarrow 0$ .

Therefore  $\max_{1 \leq j \leq p} \mathbb{E}_n[f_{ij}^4 v_{il}^4] \leq \mathbb{E}_n[v_{il}^4] \max_{1 \leq i \leq n, 1 \leq j \leq p} f_{ij}^4 \lesssim_P \log^2(p \vee n)$ . Thus, applying Lemma 4,

$$\max_{1 \leq l \leq k_e, 1 \leq j \leq p} |\mathbb{E}_n[f_{ij}^2 v_{il}^2] - \bar{\mathbb{E}}[f_{ij}^2 v_{il}^2]| \lesssim_P \log(p \vee n) \sqrt{\frac{\log(pk_e)}{n}} \lesssim_P \sqrt{\frac{\log^3(p \vee n)}{n}} \rightarrow_P 0$$

since  $\log p = o(n^{1/3})$ . The remaining moment conditions of RF(ii) follows immediately from the definition of the conditionally bounded moments since for any  $m > 0$ ,  $\bar{\mathbb{E}}[|f_{ij}|^m]$  is bounded, uniformly in  $1 \leq j \leq p$ , uniformly in  $n$ , for the i.i.d. Gaussian regressors of Lemma 1 of Belloni, Chen, Chernozhukov, and Hansen (2010). The proof of (2) for arbitrary bounded i.i.d. regressors of Lemma 2 of Belloni, Chen, Chernozhukov, and Hansen (2010) is similar.

#### APPENDIX E. PROOF OF LEMMA 4.

The first two conditions of SM(iii) follows from the assumed rate  $s^2 \log^2(p \vee n) = o(n)$  since we have  $q_e = 4$ . To show part (1), we note that by simple union bounds and tail properties of Gaussian variable, we have that  $\max_{1 \leq i \leq n, 1 \leq j \leq p} f_{ij}^2 \lesssim_P \log(p \vee n)$ , so we need  $\log(p \vee n) \frac{s \log(p \vee n)}{n} \rightarrow 0$ . Applying union bound, Gaussian concentration inequalities Ledoux and Talagrand (1991), and that  $\log^2 p = o(n)$ , we have  $\max_{1 \leq j \leq p} \mathbb{E}_n[f_{ij}^4] \lesssim_P 1$ . Thus SM(iii)(c) holds by  $\max_j \mathbb{E}_n[f_{ij}^2 \epsilon_i^2] \leq (\mathbb{E}_n[\epsilon_i^4])^{1/2} \max_{1 \leq j \leq p} (\mathbb{E}_n[f_{ij}^4])^{1/2} \lesssim_P 1$ . Part (2) follows because regressors are bounded and the moment assumption on  $\epsilon$ . □

## APPENDIX F. PROOF OF LEMMA 11.

Step 1. Here we consider the initial option, in which  $\hat{\gamma}_{jl}^2 = \mathbb{E}_n[f_{ij}^2(d_{il} - \mathbb{E}_n d_{il})^2]$ . Let us define  $\tilde{d}_{il} = d_{il} - \bar{\mathbb{E}}[d_{il}]$ ,  $\tilde{\gamma}_{jl}^2 = \mathbb{E}_n[f_{ij}^2 \tilde{d}_{il}^2]$  and  $\gamma_{jl}^2 = \bar{\mathbb{E}}[f_{ij}^2 \tilde{d}_{il}^2]$ . We want to show that

$$\Delta_1 = \max_{1 \leq l \leq k_e, 1 \leq j \leq p} |\hat{\gamma}_{jl}^2 - \tilde{\gamma}_{jl}^2| \rightarrow_P 0, \quad \Delta_2 = \max_{1 \leq l \leq k_e, 1 \leq j \leq p} |\tilde{\gamma}_{jl}^2 - \gamma_{jl}^2| \rightarrow_P 0,$$

which would imply that  $\max_{1 \leq j \leq p, 1 \leq l \leq k_e} |\hat{\gamma}_{jl}^2 - \gamma_{jl}^2| \rightarrow_P 0$  and then since  $\gamma_{jl}^2$ 's are uniformly bounded from above by Condition RF and bounded below by  $\gamma_{jl}^{02} = \bar{\mathbb{E}}[f_{ij}^2 v_{il}^2]$ , which are bounded away from zero. The asymptotic validity of the initial option then follows.

We have that  $\Delta_2 \rightarrow_P 0$  by Condition RF, and, since  $\mathbb{E}_n[\tilde{d}_{il}] = \mathbb{E}_n[d_{il}] - \bar{\mathbb{E}}[d_{il}]$ , we have

$$\begin{aligned} \Delta_1 &= \max_{1 \leq l \leq k_e, 1 \leq j \leq p} |\mathbb{E}_n[f_{ij}^2 \{(\tilde{d}_{il} - \mathbb{E}_n \tilde{d}_{il})^2 - \tilde{d}_{il}^2\}]| \\ &\leq \max_{1 \leq l \leq k_e, 1 \leq j \leq p} 2|\mathbb{E}_n[f_{ij}^2 \tilde{d}_{il}] \mathbb{E}_n[\tilde{d}_{il}]| + \max_{1 \leq l \leq k_e, 1 \leq j \leq p} |\mathbb{E}_n[f_{ij}^2] (\mathbb{E}_n \tilde{d}_{il})^2| \rightarrow_P 0. \end{aligned}$$

Indeed, we have for the first term that,

$$\max_{1 \leq l \leq k_e, 1 \leq j \leq p} |\mathbb{E}_n[f_{ij}^2 \tilde{d}_{il}] \mathbb{E}_n[\tilde{d}_{il}]| \leq \max_{i \leq n, j \leq p} |f_{ij}| \sqrt{\mathbb{E}_n[f_{ij}^2 \tilde{d}_{il}^2]} O_P(1/\sqrt{n}) \rightarrow_P 0$$

where we first used Holder inequality and  $\max_{1 \leq l \leq k_e} |\mathbb{E}_n[\tilde{d}_{il}]| \lesssim_P \sqrt{k_e}/\sqrt{n}$  by the Chebyshev inequality and by  $\bar{\mathbb{E}}[\tilde{d}_{il}^2]$  being uniformly bounded by Condition RF; then we invoked Condition RF to claim convergence to zero. Likewise, by Condition RF,

$$\max_{1 \leq l \leq k_e, 1 \leq j \leq p} |\mathbb{E}_n[f_{ij}^2] (\mathbb{E}_n \tilde{d}_{il})^2| \leq \max_{1 \leq j \leq p} |f_{ij}^2| O_P(1/n) \rightarrow_P 0.$$

Step 2. Here we consider the refined option, in which  $\hat{\gamma}_{jl}^2 = \mathbb{E}_n[f_{ij}^2 \hat{v}_{il}^2]$ . The residual here  $\hat{v}_{il} = d_{il} - \hat{D}_{il}$  can be based on any estimator that obeys

$$\max_{1 \leq l \leq k_e} \|\hat{D}_{il} - D_{il}\|_{2,n} \lesssim_P \sqrt{\frac{s \log(p \vee n)}{n}}. \quad (\text{F.46})$$

Such estimators include the Lasso and Post-Lasso estimators based on the initial option. Below we establish that the penalty levels, based on the refined option using any estimator obeying (F.46), are asymptotically valid. Thus by Theorems 1 and 2, the Lasso and Post-Lasso estimators based on the refined option also obey (F.46). This, establishes that we can iterate on the refined option a bounded number of times, without affecting the validity of the approach.

Recall that  $\hat{\gamma}_{jl}^2 = \mathbb{E}_n[f_{ij}^2 v_{il}^2]$  and define  $\gamma_{jl}^{02} := \bar{\mathbb{E}}[f_{ij}^2 v_{il}^2]$ , which is bounded away from zero and from above by assumption. Hence, by Condition RF, it suffices to show that  $\max_{1 \leq j \leq p, 1 \leq l \leq k_e} |\hat{\gamma}_{jl}^2 - \gamma_{jl}^{02}| \rightarrow_P 0$  which implies the loadings are asymptotic valid with  $u' = 1$ . This in turn follows from

$$\Delta_1 = \max_{1 \leq l \leq k_e, 1 \leq j \leq p} |\hat{\gamma}_{jl}^2 - \hat{\gamma}_{jl}^{02}| \rightarrow_P 0, \quad \Delta_2 = \max_{1 \leq l \leq k_e, 1 \leq j \leq p} |\hat{\gamma}_{jl}^{02} - \gamma_{jl}^{02}|^2 \rightarrow_P 0,$$

which we establish below.

Now note that we have proven  $\Delta_2 \rightarrow_P 0$  in the Step 3 of the proof of Theorem 1. As for  $\Delta_1$  we note that

$$\Delta_1 \leq 2 \max_{1 \leq l \leq k_e, 1 \leq j \leq p} |\mathbb{E}_n[f_{ij}^2 v_{jl}(\hat{D}_{il} - D_{il})]| + \max_{1 \leq l \leq k_e, 1 \leq j \leq p} \mathbb{E}_n[f_{ij}^2(\hat{D}_{il} - D_{il})^2].$$

The first term is bounded by Holder and Liapunov inequalities,

$$\max_{i \leq n, j \leq p} |f_{ij}|(\mathbb{E}_n[f_{ij}^2 v_{il}^2])^{1/2} \max_{l \leq k_e} \|\hat{D}_{il} - D_{il}\|_{2,n} \lesssim_P \max_{i \leq n, j \leq p} |f_{ij}|(\mathbb{E}_n[f_{ij}^2 v_{il}^2])^{1/2} \sqrt{\frac{s \log(p \vee n)}{n}} \rightarrow_P 0.$$

where the conclusion is by Condition RF. The second term is of stochastic order

$$\max_{i \leq n, j \leq p} |f_{ij}^2| \frac{s \log(p \vee n)}{n} \rightarrow_P 0,$$

which converges to zero by Condition RF.  $\square$

## APPENDIX G. ADDITIONAL SIMULATION RESULTS

In this appendix, we present simulation results to complement the results given in the paper. The simulations use the same model as the simulations in the paper:

$$\begin{aligned} y_i &= \beta x_i + e_i \\ x_i &= z_i' \Pi + v_i \end{aligned} \quad (e_i, v_i) \sim N \left( 0, \begin{pmatrix} \sigma_e^2 & \sigma_{ev} \\ \sigma_{ev} & \sigma_v^2 \end{pmatrix} \right) \text{ i.i.d.}$$

where  $\beta = 1$  is the parameter of interest, and  $z_i = (z_{i1}, z_{i2}, \dots, z_{i100})' \sim N(0, \Sigma_Z)$  is a 100 x 1 vector with  $E[z_{ih}^2] = \sigma_z^2$  and  $Corr(z_{ih}, z_{ij}) = .5^{|j-h|}$ . In all simulations, we set  $\sigma_e^2 = 2$  and  $\sigma_z^2 = 0.3$ .

For the other parameters, we consider various settings. We provide results for sample sizes,  $n$ , of 100, 250, and 500; and we consider three different values for  $Corr(e, v)$ : 0, .3, and .6. We also consider four values of  $\sigma_v^2$  which are chosen to benchmark four different strengths of instruments. The four values of  $\sigma_v^2$  are found as  $\sigma_v^2 = \frac{n \Pi' \Sigma_Z \Pi}{F^* \Pi' \Pi}$  for  $F^*$ : 2.5, 10, 40, and 160. We use two different designs for the first-stage coefficients,  $\Pi$ . The first sets the first  $S$  elements of  $\Pi$  equal to one and the remaining elements equal to zero. We refer to this design as the “cut-off” design. The second model sets the coefficient on  $z_{ih} = .7^{h-1}$  for  $h = 1, \dots, 100$ . We refer to this design as the “exponential” design. In the cut-off case, we consider  $S$  of 5, 25, 50, and 100 to cover different degrees of sparsity.

For each setting of the simulation parameter values, we report results from seven different estimation procedures. A simple possibility when presented with many instrumental variables is to just estimate the model using 2SLS and all of the available instruments. It is well-known that this will result in poor-finite sample properties unless there are many more observations than instruments; see, for example, Bekker (1994). The limited information maximum likelihood estimator (LIML) and its modification by Fuller (1977) (FULL)<sup>22</sup> are both robust to many

<sup>22</sup>Fuller (1977) requires a user-specified parameter. We set this parameter equal to one which produces a higher-order unbiased estimator.

instruments as long as the presence of many instruments is accounted for when constructing standard errors for the estimators; see Bekker (1994) and Hansen, Hausman, and Newey (2008) for example. We report results for these estimators in rows labeled 2SLS(100), LIML(100), and FULL(100) respectively.<sup>23</sup> For LASSO, we consider variable selection based on two different sets of instruments. In the first scenario, we use LASSO to select among the base 100 instruments and report results for the IV estimator based on the LASSO (LASSO) and Post-LASSO (Post-LASSO) forecasts. In the second, we use LASSO to select among 120 instruments formed by augmenting the base 100 instruments by the first 20 principle components constructed from the sampled instruments in each replication. We then report results for the IV estimator based on the LASSO (LASSO-F) and Post-LASSO (Post-LASSO-F) forecasts. In all cases, we use the refined data-dependent penalty loadings given in the paper.<sup>24</sup> For each estimator, we report root-truncated-mean-squared-error (RMSE),<sup>25</sup> median bias (Med. Bias), median absolute deviation (MAD), and rejection frequencies for 5% level tests (rp(.05)).<sup>26</sup> For computing rejection frequencies, we estimate conventional 2SLS standard errors for 2SLS(100), LASSO, and Post-LASSO, and the many instrument robust standard errors of Hansen, Hausman, and Newey (2008) for LIML(100) and FULL(100).

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<sup>23</sup>With  $n = 100$ , we randomly select 99 instruments for use in FULL(100) and LIML(100).

<sup>24</sup>Specifically, we start by finding a value of  $\lambda$  for which LASSO selected only one instrument. We used this instrument to construct an initial set of residuals for use in defining the refined penalty loadings. Using these loadings, we run another LASSO step and select a new set of instruments. We then compute another set of residuals and use these residuals to recompute the loadings. We then run a final LASSO step. We report the results for the IV estimator of  $\beta$  based on the instruments chosen in this final LASSO-step.

<sup>25</sup>We truncate the squared error at  $1e12$ .

<sup>26</sup>In cases where LASSO selects no instruments, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.

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Table 1: 2SLS Simulation Results. Exponential Design. N = 100

Estimator	Select 0	Corr( $v$ ) = 0				Corr( $v$ ) = .3				Corr( $v$ ) = .6			
		RMSE	Med. Bias	MAD	rp(.05)	RMSE	Med. Bias	MAD	rp(.05)	RMSE	Med. Bias	MAD	rp(.05)
F* = 2.5													
2SLS(100)		0.037	0.000	0.025	0.056	0.108	0.103	0.103	0.852	0.205	0.202	0.202	1.000
LIML(100)		6.836	-0.051	0.345	0.024	8.442	0.135	0.378	0.121	32.289	0.181	0.318	0.230
FULL(100)		2.753	-0.051	0.345	0.024	2.792	0.135	0.377	0.121	1.973	0.181	0.316	0.230
LASSO	499	0.059	0.059	0.059	0.000	500	*	*	0.000	500	*	*	0.000
Post-LASSO	499	0.056	0.056	0.056	0.000	500	*	*	0.000	500	*	*	0.000
LASSO-F	238	0.145	-0.004	0.084	0.022	231	0.151	0.085	0.105	0.058	0.184	0.154	0.174
Post-LASSO-F	238	0.136	0.003	0.081	0.018	231	0.144	0.081	0.101	0.060	0.177	0.146	0.188
F* = 10													
2SLS(100)		0.065	-0.003	0.043	0.058	0.176	0.168	0.168	0.758	0.335	0.335	0.335	0.998
LIML(100)		6.638	-0.039	0.479	0.038	228.717	0.113	0.527	0.122	14.189	0.298	0.588	0.210
FULL(100)		3.657	-0.039	0.479	0.038	3.889	0.113	0.526	0.122	4.552	0.298	0.588	0.210
LASSO	79	0.137	-0.008	0.087	0.034	0.136	0.047	0.081	0.056	0.142	0.051	0.094	0.104
Post-LASSO	79	0.132	-0.008	0.082	0.030	0.133	0.042	0.085	0.056	0.140	0.060	0.094	0.114
LASSO-F	9	0.152	-0.015	0.094	0.050	0.160	0.069	0.097	0.078	0.212	0.136	0.152	0.242
Post-LASSO-F	9	0.142	-0.010	0.080	0.048	0.150	0.068	0.094	0.092	0.198	0.129	0.144	0.244
F* = 40													
2SLS(100)		0.096	-0.004	0.068	0.044	0.217	0.193	0.193	0.530	0.391	0.381	0.381	0.988
LIML(100)		19.277	-0.037	0.599	0.022	21.404	0.070	0.718	0.082	6.796	0.158	0.607	0.140
FULL(100)		6.273	-0.037	0.598	0.020	6.567	0.070	0.718	0.082	5.444	0.158	0.607	0.140
LASSO	0	0.129	-0.001	0.086	0.042	0.135	0.016	0.091	0.042	0.137	0.042	0.094	0.088
Post-LASSO	0	0.126	-0.002	0.084	0.038	0.135	0.025	0.088	0.066	0.136	0.052	0.094	0.096
LASSO-F	0	0.127	0.001	0.087	0.050	0.134	0.029	0.093	0.056	0.148	0.073	0.100	0.114
Post-LASSO-F	0	0.122	0.000	0.081	0.042	0.132	0.038	0.090	0.056	0.147	0.082	0.101	0.136
F* = 160													
2SLS(100)		0.128	0.003	0.086	0.064	0.178	0.144	0.147	0.206	0.307	0.285	0.285	0.710
LIML(100)		79.113	0.014	0.540	0.038	45.371	-0.016	0.516	0.044	8.024	0.012	0.408	0.116
FULL(100)		10.092	0.014	0.540	0.038	17.107	-0.016	0.516	0.044	7.637	0.012	0.408	0.116
LASSO	0	0.139	0.001	0.093	0.054	0.129	0.009	0.087	0.048	0.136	0.023	0.087	0.086
Post-LASSO	0	0.139	-0.001	0.094	0.058	0.128	0.019	0.086	0.046	0.136	0.031	0.089	0.090
LASSO-F	0	0.138	0.000	0.092	0.036	0.128	0.018	0.090	0.044	0.139	0.038	0.089	0.094
Post-LASSO-F	0	0.137	-0.008	0.092	0.054	0.126	0.026	0.086	0.044	0.139	0.047	0.093	0.100

Note: Results are based on 500 simulation replications and 100 instruments. The first-stage coefficients were set equal  $\hat{\gamma}^{-1}$  for  $j = 1, \dots, 100$  in this design. Corr( $v$ ) is the correlation between first-stage and structural errors. F\* measures the strength of the instruments as outlined in the text. 2SLS(100), LIML(100), and FULL(100) are respectively the 2SLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.

Table 2: 2SLS Simulation Results: Exponential Design. N = 250

Estimator	Select 0	Corr( $v$ ) = 0					Corr( $v$ ) = .3					Corr( $v$ ) = .6				
		RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)	Select 0
2SLS(100)		0.023	0.001	0.016	0.054		0.068	0.064	0.064	0.858		0.131	0.129	0.129	1.000	
LIML(100)		28.982	0.009	0.158	0.032		5.126	0.034	0.152	0.050		2.201	0.072	0.145	0.130	
FULL(100)		0.310	0.009	0.151	0.030		0.272	0.034	0.144	0.048		0.266	0.076	0.134	0.130	
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
LASSO-F	409	0.070	0.015	0.044	0.002	400	0.083	0.041	0.051	0.012	399	0.115	0.106	0.106	0.088	
Post-LASSO-F	409	0.068	0.007	0.039	0.002	400	0.082	0.045	0.057	0.012	399	0.113	0.104	0.104	0.094	
F* = 10																
2SLS(100)		0.042	0.000	0.027	0.064		0.112	0.104	0.104	0.774		0.211	0.208	0.208	1.000	
LIML(100)		0.850	-0.014	0.137	0.036		0.759	0.020	0.126	0.034		1.111	0.015	0.119	0.076	
FULL(100)		0.338	-0.014	0.134	0.036		0.255	0.021	0.123	0.034		0.271	0.019	0.114	0.076	
LASSO	88	0.086	-0.001	0.060	0.036	90	0.079	0.026	0.054	0.040	78	0.092	0.046	0.067	0.128	
Post-LASSO	88	0.083	-0.002	0.058	0.034	90	0.077	0.024	0.054	0.036	78	0.092	0.052	0.069	0.144	
LASSO-F	33	0.096	-0.005	0.063	0.038	34	0.096	0.042	0.060	0.072	29	0.122	0.092	0.096	0.252	
Post-LASSO-F	33	0.091	-0.004	0.057	0.040	34	0.092	0.043	0.055	0.058	29	0.115	0.086	0.090	0.282	
F* = 40																
2SLS(100)		0.066	0.001	0.045	0.072		0.130	0.115	0.115	0.476		0.249	0.244	0.244	0.994	
LIML(100)		0.138	0.003	0.084	0.066		0.126	-0.008	0.082	0.046		0.115	-0.003	0.072	0.044	
FULL(100)		0.137	0.003	0.084	0.066		0.125	-0.007	0.081	0.044		0.114	-0.001	0.072	0.044	
LASSO	0	0.091	0.000	0.062	0.076	0	0.085	0.007	0.056	0.056	0	0.086	0.023	0.057	0.084	
Post-LASSO	0	0.089	-0.002	0.061	0.080	0	0.084	0.012	0.054	0.060	0	0.085	0.031	0.061	0.098	
LASSO-F	0	0.088	0.001	0.060	0.062	0	0.084	0.015	0.054	0.058	0	0.091	0.042	0.064	0.114	
Post-LASSO-F	0	0.086	-0.001	0.059	0.068	0	0.081	0.021	0.053	0.064	0	0.092	0.052	0.065	0.134	
F* = 160																
2SLS(100)		0.077	0.000	0.052	0.062		0.113	0.089	0.092	0.220		0.187	0.171	0.171	0.680	
LIML(100)		0.096	0.000	0.064	0.060		0.090	0.006	0.062	0.044		0.092	0.002	0.058	0.060	
FULL(100)		0.095	0.000	0.064	0.060		0.090	0.006	0.061	0.044		0.091	0.003	0.057	0.060	
LASSO	0	0.083	0.005	0.056	0.072	0	0.081	0.003	0.056	0.050	0	0.084	0.014	0.057	0.068	
Post-LASSO	0	0.082	0.006	0.054	0.070	0	0.080	0.004	0.053	0.052	0	0.085	0.018	0.058	0.076	
LASSO-F	0	0.082	0.002	0.055	0.064	0	0.081	0.009	0.051	0.050	0	0.086	0.024	0.058	0.074	
Post-LASSO-F	0	0.081	0.004	0.054	0.062	0	0.081	0.013	0.051	0.056	0	0.087	0.030	0.060	0.084	

Note: Results are based on 500 simulation replications and 100 instruments. The first-stage coefficients were set equal  $\hat{\pi}^{-1}$  for  $j = 1, \dots, 100$  in this design. Corr( $v$ ) is the correlation between first-stage and structural errors. F\* measures the strength of the instruments as outlined in the text. 2SLS(100), LIML(100), and FULL(100) are respectively the 2SLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.

Table 3: 2SLS Simulation Results. Exponential Design. N = 500

Estimator	Select 0	Corr( $v$ ) = 0					Corr( $v$ ) = .3					Corr( $v$ ) = .6				
		RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)	Select 0
2SLS(100)		0.016	0.002	0.010	0.050		0.047	0.045	0.045	0.828		0.093	0.093	0.093	1.000	
LIML(100)		1.085	0.020	0.116	0.034		1.899	0.011	0.102	0.052		2.729	0.038	0.103	0.122	
FULL(100)		0.188	0.019	0.103	0.030		0.165	0.013	0.093	0.046		0.166	0.042	0.092	0.122	
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
LASSO-F	461	0.046	0.001	0.026	0.000	463	0.054	0.011	0.035	0.002	467	0.080	0.065	0.065	0.028	
Post-LASSO-F	461	0.045	0.003	0.030	0.000	463	0.048	0.011	0.033	0.004	467	0.074	0.067	0.067	0.030	
F* = 10																
2SLS(100)		0.028	-0.002	0.019	0.052		0.079	0.074	0.074	0.758		0.152	0.150	0.150	1.000	
LIML(100)		0.681	-0.012	0.085	0.026		2.662	0.003	0.082	0.040		7.405	0.004	0.077	0.068	
FULL(100)		0.191	-0.011	0.083	0.020		0.182	0.005	0.079	0.036		0.154	0.008	0.073	0.070	
LASSO	119	0.061	-0.005	0.038	0.036	105	0.059	0.016	0.041	0.040	106	0.066	0.037	0.048	0.124	
Post-LASSO	119	0.059	-0.005	0.037	0.030	105	0.057	0.015	0.040	0.038	106	0.065	0.038	0.048	0.132	
LASSO-F	46	0.063	-0.001	0.039	0.024	52	0.063	0.030	0.040	0.048	46	0.084	0.063	0.066	0.222	
Post-LASSO-F	46	0.059	-0.004	0.037	0.026	52	0.059	0.027	0.039	0.060	46	0.078	0.061	0.064	0.236	
F* = 40																
2SLS(100)		0.045	0.002	0.030	0.074		0.095	0.085	0.085	0.532		0.176	0.172	0.172	0.988	
LIML(100)		0.085	0.004	0.054	0.060		0.084	0.003	0.049	0.044		0.072	0.008	0.044	0.064	
FULL(100)		0.084	0.004	0.053	0.058		0.083	0.004	0.049	0.044		0.072	0.010	0.044	0.064	
LASSO	0	0.060	0.001	0.040	0.060	0	0.058	0.006	0.036	0.048	0	0.060	0.019	0.041	0.078	
Post-LASSO	0	0.058	0.002	0.039	0.054	0	0.057	0.007	0.037	0.050	0	0.061	0.020	0.042	0.078	
LASSO-F	0	0.058	0.000	0.040	0.052	0	0.059	0.010	0.040	0.048	0	0.064	0.031	0.045	0.112	
Post-LASSO-F	0	0.057	0.001	0.038	0.050	0	0.057	0.013	0.038	0.070	0	0.066	0.033	0.044	0.156	
F* = 160																
2SLS(100)		0.054	0.004	0.036	0.066		0.082	0.063	0.064	0.246		0.134	0.124	0.124	0.684	
LIML(100)		0.065	0.006	0.045	0.058		0.069	0.000	0.046	0.058		0.063	0.002	0.045	0.048	
FULL(100)		0.065	0.006	0.045	0.054		0.068	0.001	0.045	0.058		0.063	0.003	0.045	0.048	
LASSO	0	0.060	0.003	0.042	0.054	0	0.059	0.006	0.039	0.066	0	0.059	0.010	0.040	0.070	
Post-LASSO	0	0.060	0.003	0.040	0.054	0	0.059	0.007	0.040	0.054	0	0.059	0.010	0.041	0.068	
LASSO-F	0	0.060	0.004	0.042	0.058	0	0.060	0.010	0.039	0.066	0	0.061	0.017	0.041	0.082	
Post-LASSO-F	0	0.059	0.003	0.040	0.058	0	0.059	0.012	0.039	0.062	0	0.061	0.021	0.041	0.090	

Note: Results are based on 500 simulation replications and 100 instruments. The first-stage coefficients were set equal  $\cdot J^{-1}$  for  $j = 1, \dots, 100$  in this design. Corr( $v$ ) is the correlation between first-stage and structural errors. F\* measures the strength of the instruments as outlined in the text. 2SLS(100), LIML(100), and FULL(100) are respectively the 2SLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.

Table 4: 2SLS Simulation Results. Cut-Off Design,  $S = 5$ ,  $N = 100$

Estimator	Select 0	Corr( $v$ ) = 0				Corr( $v$ ) = .3				Corr( $v$ ) = .6					
		RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)
F* = 2.5															
2SLS(100)		0.026	0.000	0.018	0.054	0.077	0.073	0.073	0.812	0.146	0.144	0.144	1.000		
LIML(100)		46.872	0.013	0.257	0.018	48.070	0.067	0.226	0.122	1.851	0.141	0.235	0.235		
FULL(100)		2.298	0.013	0.257	0.018	1.447	0.067	0.226	0.122	1.307	0.141	0.235	0.235		
LASSO	500	*	*	*	0.000	500	*	*	0.000	500	*	*	0.000		
Post-LASSO	500	*	*	*	0.000	500	*	*	0.000	500	*	*	0.000		
LASSO-F	395	0.088	-0.002	0.063	0.012	391	0.090	0.047	0.065	0.020	396	0.113	0.090	0.058	
Post-LASSO-F	395	0.080	-0.002	0.048	0.010	391	0.085	0.045	0.053	0.026	396	0.110	0.090	0.092	
F* = 10															
2SLS(100)		0.044	-0.001	0.032	0.040	0.121	0.110	0.110	0.728	0.224	0.221	0.221	1.000		
LIML(100)		57.489	0.009	0.385	0.022	13.839	0.095	0.373	0.124	13.556	0.191	0.397	0.194		
FULL(100)		2.170	0.009	0.385	0.022	5.258	0.095	0.373	0.124	2.386	0.191	0.396	0.194		
LASSO	206	0.082	-0.008	0.055	0.028	232	0.086	0.027	0.058	0.034	215	0.084	0.046	0.059	
Post-LASSO	206	0.081	-0.007	0.052	0.036	232	0.087	0.026	0.059	0.048	215	0.082	0.040	0.058	
LASSO-F	27	0.089	-0.001	0.051	0.040	22	0.105	0.042	0.065	0.084	34	0.115	0.082	0.088	
Post-LASSO-F	27	0.081	-0.001	0.047	0.050	22	0.096	0.040	0.060	0.090	34	0.109	0.079	0.081	
F* = 40															
2SLS(100)		0.066	-0.007	0.046	0.064	0.126	0.110	0.110	0.432	0.229	0.221	0.221	0.948		
LIML(100)		16.626	0.007	0.358	0.030	5.794	0.098	0.367	0.060	2.223	0.054	0.295	0.144		
FULL(100)		4.540	0.007	0.358	0.030	5.405	0.098	0.367	0.060	2.129	0.054	0.295	0.144		
LASSO	0	0.079	-0.009	0.053	0.040	0	0.079	0.012	0.051	0.046	0	0.084	0.019	0.056	
Post-LASSO	0	0.078	-0.009	0.054	0.044	0	0.078	0.012	0.051	0.046	0	0.081	0.014	0.055	
LASSO-F	0	0.080	-0.006	0.054	0.048	0	0.082	0.021	0.054	0.060	0	0.091	0.041	0.062	
Post-LASSO-F	0	0.077	-0.009	0.054	0.046	0	0.080	0.023	0.052	0.056	0	0.087	0.041	0.060	
F* = 160															
2SLS(100)		0.073	0.003	0.049	0.054	0.106	0.073	0.078	0.190	0.160	0.146	0.146	0.534		
LIML(100)		2.958	0.037	0.246	0.034	9.206	0.010	0.268	0.048	23.035	0.007	0.237	0.064		
FULL(100)		2.885	0.037	0.245	0.034	3.339	0.010	0.268	0.048	7.825	0.007	0.237	0.064		
LASSO	0	0.077	0.001	0.050	0.046	0	0.079	0.005	0.053	0.060	0	0.074	0.005	0.049	
Post-LASSO	0	0.076	0.000	0.051	0.044	0	0.079	0.005	0.054	0.058	0	0.074	0.004	0.049	
LASSO-F	0	0.077	0.001	0.050	0.046	0	0.080	0.010	0.054	0.062	0	0.075	0.018	0.051	
Post-LASSO-F	0	0.076	-0.001	0.049	0.046	0	0.079	0.010	0.054	0.060	0	0.075	0.014	0.051	

Note: Results are based on 500 simulation replications and 100 instruments. The first 5 first-stage coefficients were set equal to one and the remaining 95 to zero in this design. Corr( $v$ ) is the correlation between first-stage and structural errors.  $F^*$  measures the strength of the instruments as outlined in the text. 2SLS(100), LIML(100), and FULL(100) are respectively the 2SLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.

Table 5: 2SLS Simulation Results. Cut-Off Design,  $S = 5$ ,  $N = 250$ 

Estimator	Select 0	Corr( $e$ , $v$ ) = 0				Corr( $e$ , $v$ ) = .3				Corr( $e$ , $v$ ) = .6					
		RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)
F* = 2.5															
2SLS(100)		0.016	0.001	0.010	0.040		0.049	0.047	0.047	0.844		0.094	0.093	0.093	1.000
LIML(100)		1.295	-0.001	0.088	0.028		1.612	0.016	0.100	0.044		10.351	0.026	0.082	0.128
FULL(100)		0.202	-0.001	0.085	0.026		0.215	0.017	0.095	0.040		0.165	0.029	0.079	0.126
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	491	0.049	-0.029	0.033	0.002	493	0.057	0.047	0.047	0.000	491	0.073	0.063	0.063	0.008
Post-LASSO-F	491	0.042	-0.010	0.027	0.002	493	0.056	0.045	0.045	0.004	491	0.073	0.056	0.056	0.008
F* = 10															
2SLS(100)		0.029	-0.002	0.019	0.056		0.075	0.071	0.071	0.718		0.141	0.139	0.139	0.998
LIML(100)		0.555	0.000	0.074	0.034		3.082	0.006	0.071	0.038		0.136	0.001	0.057	0.070
FULL(100)		0.157	0.000	0.073	0.034		0.163	0.007	0.070	0.038		0.121	0.004	0.056	0.072
LASSO	239	0.052	-0.002	0.037	0.024	253	0.051	0.020	0.036	0.038	249	0.050	0.029	0.038	0.050
Post-LASSO	239	0.049	-0.003	0.037	0.024	253	0.050	0.019	0.036	0.046	249	0.048	0.025	0.037	0.050
LASSO-F	83	0.059	-0.003	0.036	0.036	88	0.058	0.021	0.036	0.074	78	0.067	0.050	0.053	0.160
Post-LASSO-F	83	0.053	-0.005	0.036	0.032	88	0.055	0.022	0.036	0.076	78	0.061	0.048	0.049	0.170
F* = 40															
2SLS(100)		0.040	0.001	0.027	0.054		0.079	0.070	0.070	0.416		0.142	0.138	0.138	0.964
LIML(100)		0.068	-0.002	0.043	0.048		0.069	0.000	0.046	0.044		0.058	-0.001	0.036	0.024
FULL(100)		0.067	-0.002	0.043	0.048		0.069	0.001	0.046	0.044		0.057	0.001	0.036	0.022
LASSO	0	0.048	0.002	0.032	0.042	0	0.049	0.005	0.034	0.042	0	0.048	0.014	0.035	0.058
Post-LASSO	0	0.048	0.001	0.032	0.036	0	0.049	0.004	0.033	0.052	0	0.048	0.012	0.033	0.056
LASSO-F	0	0.048	0.001	0.033	0.040	0	0.050	0.013	0.033	0.050	0	0.052	0.025	0.038	0.076
Post-LASSO-F	0	0.047	0.001	0.032	0.042	0	0.049	0.011	0.033	0.056	0	0.051	0.026	0.038	0.082
F* = 160															
2SLS(100)		0.045	-0.001	0.030	0.042		0.063	0.045	0.047	0.158		0.104	0.096	0.096	0.560
LIML(100)		0.054	0.000	0.036	0.048		0.054	0.000	0.036	0.048		0.051	0.001	0.035	0.036
FULL(100)		0.053	0.000	0.036	0.048		0.054	0.001	0.036	0.046		0.051	0.001	0.034	0.036
LASSO	0	0.047	0.001	0.030	0.048	0	0.048	0.004	0.032	0.048	0	0.049	0.007	0.033	0.050
Post-LASSO	0	0.047	0.000	0.031	0.046	0	0.048	0.004	0.031	0.042	0	0.049	0.007	0.032	0.050
LASSO-F	0	0.047	0.000	0.030	0.056	0	0.049	0.006	0.032	0.048	0	0.049	0.011	0.034	0.056
Post-LASSO-F	0	0.047	-0.001	0.030	0.050	0	0.048	0.005	0.031	0.052	0	0.049	0.013	0.033	0.058

Note: Results are based on 500 simulation replications and 100 instruments. The first 5 first-stage coefficients were set equal to one and the remaining 95 to zero in this design. Corr( $e$ ,  $v$ ) is the correlation between first-stage and structural errors.  $F^*$  measures the strength of the instruments as outlined in the text. 2SLS(100), LIML(100), and FULL(100) are respectively the 2SLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.

Table 6: 2SLS Simulation Results. Cut-Off Design,  $S = 5$ ,  $N = 500$ 

Estimator	Select 0	Corr( $v$ ) = 0					Corr( $v$ ) = .3					Corr( $v$ ) = .6				
		RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)	Select 0
2SLS(100)		0.012	0.001	0.008	0.052		0.034	0.032	0.032	0.838		0.066	0.065	0.065	1.000	
LIML(100)		2.472	0.006	0.062	0.024		3.056	0.004	0.067	0.060		1.026	0.017	0.059	0.120	
FULL(100)		0.122	0.006	0.058	0.022		0.127	0.005	0.059	0.056		0.106	0.021	0.055	0.122	
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	498	0.040	0.039	0.039	0.000	
Post-LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	498	0.037	0.037	0.037	0.000	
$F^* = 10$																
2SLS(100)		0.020	0.000	0.014	0.050		0.053	0.050	0.050	0.750		0.097	0.096	0.096	0.996	
LIML(100)		0.205	0.001	0.047	0.044		0.127	0.004	0.048	0.056		0.072	-0.001	0.037	0.060	
FULL(100)		0.100	0.001	0.047	0.040		0.088	0.005	0.047	0.050		0.067	0.002	0.038	0.060	
LASSO	300	0.032	0.000	0.021	0.008	306	0.034	0.012	0.024	0.022	324	0.036	0.021	0.025	0.042	
Post-LASSO	300	0.030	-0.001	0.021	0.014	306	0.034	0.014	0.024	0.030	324	0.034	0.019	0.023	0.044	
LASSO-F	121	0.036	-0.002	0.023	0.020	136	0.038	0.017	0.026	0.042	118	0.043	0.030	0.033	0.140	
Post-LASSO-F	121	0.034	0.002	0.019	0.016	136	0.037	0.016	0.026	0.070	118	0.041	0.029	0.031	0.154	
$F^* = 40$																
2SLS(100)		0.027	-0.003	0.019	0.044		0.056	0.048	0.048	0.426		0.099	0.097	0.097	0.950	
LIML(100)		0.044	-0.001	0.030	0.036		0.043	0.001	0.029	0.034		0.041	-0.001	0.026	0.040	
FULL(100)		0.044	-0.001	0.030	0.036		0.043	0.002	0.029	0.036		0.041	0.000	0.026	0.040	
LASSO	0	0.034	0.000	0.022	0.048	0	0.033	0.009	0.023	0.040	0	0.035	0.009	0.023	0.066	
Post-LASSO	0	0.034	-0.002	0.023	0.044	0	0.032	0.006	0.023	0.036	0	0.034	0.008	0.023	0.064	
LASSO-F	0	0.034	0.000	0.023	0.050	0	0.034	0.011	0.025	0.040	0	0.036	0.016	0.024	0.086	
Post-LASSO-F	0	0.034	-0.002	0.023	0.048	0	0.033	0.010	0.023	0.046	0	0.036	0.016	0.025	0.084	
$F^* = 160$																
2SLS(100)		0.033	-0.005	0.021	0.058		0.047	0.035	0.035	0.188		0.071	0.064	0.064	0.536	
LIML(100)		0.037	-0.003	0.024	0.046		0.036	0.003	0.025	0.044		0.036	-0.001	0.024	0.040	
FULL(100)		0.037	-0.003	0.024	0.046		0.036	0.003	0.025	0.044		0.036	0.000	0.024	0.040	
LASSO	0	0.034	-0.004	0.025	0.048	0	0.034	0.005	0.025	0.030	0	0.034	0.003	0.024	0.048	
Post-LASSO	0	0.034	-0.004	0.025	0.046	0	0.034	0.005	0.025	0.030	0	0.034	0.003	0.024	0.046	
LASSO-F	0	0.034	-0.005	0.024	0.050	0	0.034	0.007	0.025	0.032	0	0.035	0.008	0.024	0.050	
Post-LASSO-F	0	0.034	-0.005	0.023	0.052	0	0.034	0.007	0.025	0.032	0	0.035	0.009	0.023	0.052	

Note: Results are based on 500 simulation replications and 100 instruments. The first 5 first-stage coefficients were set equal to one and the remaining 95 to zero in this design. Corr( $v$ ) is the correlation between first-stage and structural errors.  $F^*$  measures the strength of the instruments as outlined in the text. 2SLS(100), LIML(100), and FULL(100) are respectively the 2SLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.

Table 7: 2SLS Simulation Results. Cut-Off Design,  $S = 25$ .  $N = 100$ 

Estimator	Select 0	Corr( $e, y$ ) = 0				Corr( $e, y$ ) = .3				Corr( $e, y$ ) = .6					
		RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)
F* = 2.5															
2SLS(100)		0.020	0.000	0.013	0.044		0.048	0.045	0.045	0.678		0.090	0.088	0.088	1.000
LIML(100)		4.259	0.013	0.150	0.020		5.353	0.027	0.141	0.102		1.394	0.063	0.137	0.205
FULL(100)		1.615	0.013	0.150	0.020		1.394	0.027	0.141	0.102		1.268	0.063	0.137	0.205
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	486	0.043	0.018	0.034	0.002	493	0.024	0.009	0.025	0.000	486	0.032	0.013	0.028	0.000
Post-LASSO-F	486	0.044	-0.011	0.032	0.000	493	0.022	-0.018	0.018	0.000	486	0.027	0.016	0.022	0.000
F* = 10															
2SLS(100)		0.026	-0.002	0.018	0.054		0.049	0.042	0.042	0.386		0.087	0.083	0.083	0.906
LIML(100)		1.269	-0.001	0.138	0.026		2.468	0.018	0.142	0.086		4.565	0.038	0.139	0.136
FULL(100)		1.181	-0.001	0.138	0.026		1.616	0.018	0.142	0.086		2.000	0.039	0.139	0.136
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	55	0.037	-0.005	0.024	0.038	46	0.038	0.006	0.023	0.058	46	0.041	0.011	0.027	0.074
Post-LASSO-F	55	0.035	-0.004	0.022	0.052	46	0.035	0.008	0.024	0.058	46	0.040	0.015	0.028	0.078
F* = 40															
2SLS(100)		0.031	-0.002	0.020	0.076		0.040	0.027	0.029	0.170		0.061	0.053	0.053	0.448
LIML(100)		3.549	0.007	0.088	0.034		2.640	0.021	0.092	0.040		1.916	0.008	0.078	0.088
FULL(100)		2.810	0.007	0.088	0.034		2.333	0.021	0.092	0.040		1.837	0.008	0.078	0.088
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	3	0.038	-0.001	0.025	0.058	1	0.036	0.007	0.024	0.054	0	0.040	0.011	0.028	0.086
Post-LASSO-F	3	0.036	-0.005	0.024	0.066	1	0.034	0.008	0.023	0.056	0	0.037	0.011	0.025	0.082
F* = 160															
2SLS(100)		0.032	-0.001	0.022	0.050		0.032	0.014	0.023	0.072		0.041	0.029	0.031	0.176
LIML(100)		2.393	0.005	0.055	0.020		1.946	0.001	0.058	0.022		1.295	-0.001	0.053	0.030
FULL(100)		2.375	0.005	0.055	0.020		1.932	0.001	0.058	0.022		1.289	-0.001	0.053	0.030
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	499	0.055	0.055	0.055	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	499	0.049	0.049	0.049	0.000
LASSO-F	0	0.038	-0.001	0.025	0.050	0	0.035	0.003	0.023	0.060	0	0.035	0.006	0.024	0.036
Post-LASSO-F	0	0.036	-0.003	0.024	0.060	0	0.032	0.002	0.021	0.046	0	0.034	0.005	0.022	0.048

Note: Results are based on 500 simulation replications and 100 instruments. The first 25 first-stage coefficients were set equal to one and the remaining 75 to zero in this design. Corr( $e, y$ ) is the correlation between first-stage and structural errors. F\* measures the strength of the instruments as outlined in the text. 2SLS(100), LIML(100), and FULL(100) are respectively the 2SLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.



Table 8: 2SLS Simulation Results. Cut-Off Design,  $S = 25$ .  $N = 250$ 

Estimator	Select 0	Corr( $\epsilon, y$ ) = 0				Select 0	Corr( $\epsilon, y$ ) = .3				Select 0	Corr( $\epsilon, y$ ) = .6			
		RMSE	Med. Bias	MAD	rp(.05)		RMSE	Med. Bias	MAD	rp(.05)		RMSE	Med. Bias	MAD	rp(.05)
F* = 2.5															
2SLS(100)		0.012	0.000	0.008	0.052	0.031	0.029	0.029	0.712	0.058	0.057	0.057	1.000		
LIML(100)		0.355	0.000	0.024	0.054	1.183	0.002	0.025	0.034	0.045	0.002	0.020	0.058		
FULL(100)		0.052	0.000	0.023	0.050	0.047	0.002	0.025	0.034	0.040	0.003	0.020	0.058		
LASSO	500	*	*	*	0.000	500	*	*	0.000	500	*	*	0.000		
Post-LASSO	500	*	*	*	0.000	500	*	*	0.000	500	*	*	0.000		
LASSO-F	499	0.000	0.000	0.000	0.000	499	0.014	-0.014	0.014	0.000	500	*	0.000		
Post-LASSO-F	499	0.003	0.003	0.003	0.000	499	0.007	0.007	0.007	0.000	500	*	0.000		
F* = 10															
2SLS(100)		0.017	0.001	0.012	0.044	0.030	0.027	0.027	0.406	0.054	0.052	0.052	0.908		
LIML(100)		0.026	0.001	0.018	0.040	0.024	0.001	0.018	0.036	0.025	0.000	0.015	0.054		
FULL(100)		0.026	0.001	0.018	0.040	0.024	0.001	0.018	0.036	0.024	0.000	0.015	0.052		
LASSO	500	*	*	*	0.000	500	*	*	0.000	500	*	*	0.000		
Post-LASSO	500	*	*	*	0.000	500	*	*	0.000	500	*	*	0.000		
LASSO-F	1	0.022	-0.001	0.015	0.050	0	0.022	0.006	0.014	0.044	1	0.024	0.009		
Post-LASSO-F	1	0.021	0.000	0.014	0.046	0	0.021	0.008	0.015	0.054	1	0.023	0.012		
F* = 40															
2SLS(100)		0.018	0.001	0.012	0.048	0.026	0.018	0.019	0.176	0.038	0.034	0.034	0.468		
LIML(100)		0.021	0.001	0.013	0.052	0.022	0.001	0.015	0.056	0.022	0.000	0.014	0.054		
FULL(100)		0.021	0.001	0.013	0.052	0.022	0.001	0.015	0.056	0.022	0.000	0.014	0.054		
LASSO	359	0.020	0.006	0.015	0.002	348	0.023	0.007	0.017	0.022	356	0.023	0.007		
Post-LASSO	359	0.019	0.005	0.013	0.008	348	0.022	0.004	0.016	0.020	356	0.022	0.006		
LASSO-F	0	0.021	0.001	0.015	0.048	0	0.022	0.005	0.016	0.056	0	0.022	0.007		
Post-LASSO-F	0	0.020	0.002	0.013	0.052	0	0.022	0.006	0.017	0.068	0	0.022	0.009		
F* = 160															
2SLS(100)		0.019	-0.001	0.013	0.040	0.022	0.010	0.016	0.088	0.027	0.018	0.019	0.188		
LIML(100)		0.019	0.000	0.013	0.036	0.020	0.001	0.014	0.058	0.020	0.000	0.013	0.074		
FULL(100)		0.019	0.000	0.013	0.036	0.020	0.001	0.014	0.058	0.020	0.000	0.013	0.074		
LASSO	51	0.020	-0.001	0.015	0.040	47	0.021	0.004	0.014	0.044	37	0.022	0.007		
Post-LASSO	51	0.020	-0.001	0.013	0.026	47	0.020	0.004	0.014	0.048	37	0.021	0.006		
LASSO-F	0	0.020	-0.001	0.014	0.042	0	0.022	0.002	0.015	0.058	0	0.021	0.003		
Post-LASSO-F	0	0.020	-0.001	0.013	0.040	0	0.021	0.003	0.014	0.050	0	0.021	0.006		

Note: Results are based on 500 simulation replications and 100 instruments. The first 25 first-stage coefficients were set equal to one and the remaining 75 to zero in this design. Corr( $\epsilon, y$ ) is the correlation between first-stage and structural errors.  $F^*$  measures the strength of the instruments as outlined in the text. 2SLS(100), LIML(100), and FULL(100) are respectively the 2SLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.

Table 9: 2SLS Simulation Results. Cut-Off Design,  $S = 25$ .  $N = 500$ 

Estimator	Select 0	Corr( $\epsilon, y$ ) = 0				Select 0	Corr( $\epsilon, y$ ) = .3				Select 0	Corr( $\epsilon, y$ ) = .6			
		RMSE	Med. Bias	MAD	rp(.05)		RMSE	Med. Bias	MAD	rp(.05)		RMSE	Med. Bias	MAD	rp(.05)
F* = 2.5															
2SLS(100)		0.009	0.000	0.006	0.052		0.021	0.020	0.020	0.652		0.041	0.040	0.040	0.998
LIML(100)		0.036	0.001	0.016	0.044		0.071	-0.001	0.016	0.042		0.025	0.000	0.013	0.052
FULL(100)		0.031	0.001	0.016	0.042		0.030	-0.001	0.016	0.040		0.023	0.001	0.013	0.054
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
F* = 10															
2SLS(100)		0.012	0.000	0.008	0.046		0.022	0.019	0.019	0.406		0.037	0.036	0.036	0.888
LIML(100)		0.017	-0.001	0.011	0.044		0.017	0.000	0.012	0.044		0.017	-0.001	0.012	0.040
FULL(100)		0.017	-0.001	0.011	0.044		0.017	0.000	0.012	0.044		0.017	-0.001	0.012	0.040
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	0	0.014	0.000	0.009	0.048	0	0.015	0.004	0.011	0.066	0	0.016	0.006	0.010	0.096
Post-LASSO-F	0	0.014	-0.001	0.008	0.060	0	0.015	0.004	0.010	0.078	0	0.017	0.009	0.011	0.144
F* = 40															
2SLS(100)		0.013	-0.001	0.009	0.044		0.017	0.012	0.013	0.160		0.026	0.022	0.022	0.426
LIML(100)		0.014	-0.002	0.010	0.034		0.015	0.000	0.009	0.046		0.014	-0.001	0.009	0.056
FULL(100)		0.014	-0.002	0.010	0.034		0.014	0.000	0.009	0.048		0.014	0.000	0.009	0.056
LASSO	0	0.014	0.000	0.010	0.038	0	0.014	0.004	0.009	0.056	0	0.016	0.009	0.012	0.108
Post-LASSO	0	0.013	0.000	0.009	0.040	0	0.014	0.003	0.009	0.056	0	0.015	0.007	0.010	0.090
LASSO-F	0	0.014	0.000	0.010	0.040	0	0.014	0.002	0.009	0.048	0	0.015	0.004	0.010	0.064
Post-LASSO-F	0	0.014	-0.001	0.010	0.044	0	0.014	0.003	0.009	0.042	0	0.015	0.007	0.010	0.092
F* = 160															
2SLS(100)		0.014	0.000	0.010	0.062		0.015	0.007	0.011	0.080		0.018	0.013	0.014	0.138
LIML(100)		0.014	0.000	0.010	0.062		0.014	0.001	0.010	0.048		0.013	0.000	0.009	0.036
FULL(100)		0.014	0.000	0.010	0.062		0.014	0.001	0.010	0.048		0.013	0.000	0.009	0.036
LASSO	0	0.014	-0.001	0.010	0.060	0	0.014	0.002	0.009	0.056	0	0.014	0.005	0.010	0.064
Post-LASSO	0	0.014	-0.001	0.010	0.068	0	0.014	0.002	0.009	0.054	0	0.014	0.004	0.010	0.056
LASSO-F	0	0.014	0.000	0.010	0.056	0	0.014	0.001	0.010	0.048	0	0.014	0.003	0.010	0.052
Post-LASSO-F	0	0.014	-0.001	0.010	0.056	0	0.014	0.002	0.010	0.054	0	0.014	0.005	0.010	0.064

Note: Results are based on 500 simulation replications and 100 instruments. The first 25 first-stage coefficients were set equal to one and the remaining 75 to zero in this design. Corr( $\epsilon, y$ ) is the correlation between first-stage and structural errors. F\* measures the strength of the instruments as outlined in the text. 2SLS(100), LIML(100), and FULL(100) are respectively the 2SLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.

Table 10: 2SLS Simulation Results. Cut-Off Design,  $S = 50$ ,  $N = 100$

Estimator	Select 0	Corr( $e, y$ ) = 0				Corr( $e, y$ ) = .3				Corr( $e, y$ ) = .6					
		RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)
F* = 2.5															
2SLS(100)		0.017	0.000	0.012	0.058		0.036	0.032	0.032	0.546		0.065	0.063	0.063	0.988
LIML(100)		1.649	0.005	0.108	0.016		25.295	0.014	0.101	0.090		74.420	0.038	0.096	0.165
FULL(100)		1.204	0.005	0.108	0.016		1.580	0.014	0.101	0.090		0.884	0.038	0.096	0.165
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
F* = 10															
2SLS(100)		0.019	-0.002	0.013	0.050		0.031	0.024	0.024	0.256		0.052	0.049	0.049	0.702
LIML(100)		4.640	-0.003	0.082	0.016		1.284	0.004	0.079	0.062		5.798	0.016	0.080	0.098
FULL(100)		2.054	-0.003	0.082	0.016		1.156	0.004	0.079	0.062		1.542	0.016	0.080	0.098
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	472	0.030	-0.001	0.025	0.002	468	0.032	-0.001	0.019	0.006	477	0.022	-0.007	0.017	0.000
Post-LASSO-F	472	0.030	-0.007	0.023	0.004	468	0.031	0.002	0.016	0.008	477	0.024	-0.005	0.014	0.002
F* = 40															
2SLS(100)		0.023	-0.001	0.017	0.064		0.026	0.015	0.018	0.114		0.034	0.027	0.027	0.264
LIML(100)		0.374	0.003	0.046	0.034		0.662	0.012	0.049	0.034		0.495	0.002	0.041	0.058
FULL(100)		0.374	0.003	0.046	0.034		0.657	0.012	0.049	0.034		0.495	0.002	0.041	0.058
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	400	0.028	-0.005	0.019	0.014	400	0.027	0.004	0.018	0.006	391	0.031	0.001	0.024	0.010
Post-LASSO-F	400	0.027	-0.006	0.019	0.014	400	0.025	0.004	0.016	0.010	391	0.028	0.002	0.017	0.014
F* = 160															
2SLS(100)		0.022	0.000	0.014	0.056		0.022	0.008	0.015	0.068		0.025	0.014	0.017	0.110
LIML(100)		0.419	0.002	0.031	0.026		1.272	0.000	0.033	0.018		4.169	-0.001	0.032	0.038
FULL(100)		0.419	0.002	0.031	0.026		1.224	0.000	0.033	0.018		4.017	-0.001	0.032	0.038
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	356	0.025	-0.003	0.018	0.010	357	0.026	0.002	0.017	0.014	350	0.023	-0.001	0.015	0.006
Post-LASSO-F	356	0.025	-0.001	0.017	0.016	357	0.023	0.002	0.017	0.012	350	0.023	-0.001	0.016	0.006

Note: Results are based on 500 simulation replications and 100 instruments. The first 50 first-stage coefficients were set equal to one and the remaining 50 to zero in this design. Corr( $e, y$ ) is the correlation between first-stage and structural errors.  $F^*$  measures the strength of the instruments as outlined in the text. 2SLS(100), LIML(100), and FULL(100) are respectively the 2SLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.

Table 11: 2SLS Simulation Results. Cut-Off Design,  $S = 50$ ,  $N = 250$ 

Estimator	Select 0	Corr( $\epsilon, y$ ) = 0				Select 0	Corr( $\epsilon, y$ ) = .3				Select 0	Corr( $\epsilon, y$ ) = .6			
		RMSE	Med. Bias	MAD	rp(.05)		RMSE	Med. Bias	MAD	rp(.05)		RMSE	Med. Bias	MAD	rp(.05)
F* = 2.5															
2SLS(100)		0.010	0.001	0.007	0.062		0.023	0.021	0.021	0.594		0.042	0.041	0.041	0.990
LIML(100)		0.023	0.001	0.014	0.060		0.021	0.002	0.013	0.020		0.020	0.002	0.013	0.036
FULL(100)		0.023	0.001	0.014	0.060		0.021	0.002	0.013	0.020		0.020	0.002	0.012	0.036
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
F* = 10															
2SLS(100)		0.012	0.000	0.009	0.038		0.019	0.015	0.015	0.248		0.032	0.030	0.030	0.712
LIML(100)		0.016	0.000	0.012	0.046		0.015	0.000	0.011	0.032		0.016	0.000	0.010	0.058
FULL(100)		0.016	0.000	0.012	0.046		0.015	0.000	0.011	0.032		0.016	0.000	0.010	0.060
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	85	0.015	0.001	0.011	0.030	92	0.014	0.001	0.009	0.028	94	0.015	0.003	0.010	0.042
Post-LASSO-F	85	0.014	0.001	0.010	0.032	92	0.013	0.002	0.009	0.030	94	0.015	0.004	0.011	0.046
F* = 40															
2SLS(100)		0.013	0.000	0.009	0.054		0.016	0.010	0.012	0.106		0.021	0.017	0.017	0.278
LIML(100)		0.014	0.001	0.009	0.050		0.014	0.001	0.010	0.048		0.014	-0.001	0.010	0.048
FULL(100)		0.014	0.001	0.009	0.050		0.014	0.001	0.010	0.048		0.014	-0.001	0.010	0.048
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	1	0.015	0.000	0.009	0.058	0	0.015	0.001	0.010	0.050	0	0.015	0.002	0.009	0.064
Post-LASSO-F	1	0.014	0.001	0.009	0.068	0	0.015	0.002	0.010	0.056	0	0.014	0.003	0.009	0.048
F* = 160															
2SLS(100)		0.013	0.000	0.009	0.044		0.015	0.005	0.010	0.082		0.017	0.010	0.012	0.112
LIML(100)		0.014	0.000	0.009	0.046		0.014	0.000	0.010	0.050		0.014	0.001	0.009	0.054
FULL(100)		0.014	0.000	0.009	0.046		0.014	0.000	0.010	0.050		0.014	0.001	0.009	0.052
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	0	0.015	0.000	0.010	0.058	0	0.015	0.002	0.010	0.062	0	0.015	0.001	0.010	0.048
Post-LASSO-F	0	0.014	0.000	0.009	0.056	0	0.015	0.002	0.010	0.048	0	0.014	0.002	0.009	0.052

Note: Results are based on 500 simulation replications and 100 instruments. The first 50 first-stage coefficients were set equal to one and the remaining 50 to zero in this design. Corr( $\epsilon, y$ ) is the correlation between first-stage and structural errors.  $F^*$  measures the strength of the instruments as outlined in the text. 2SLS(100), LIML(100), and FULL(100) are respectively the 2SLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.

Table 12: 2SLS Simulation Results. Cut-Off Design,  $S = 50$ ,  $N = 500$ 

Estimator	Select 0	Corr( $\epsilon, y$ ) = 0				Select 0	Corr( $\epsilon, y$ ) = .3				Select 0	Corr( $\epsilon, y$ ) = .6			
		RMSE	Med. Bias	MAD	rp(.05)		RMSE	Med. Bias	MAD	rp(.05)		RMSE	Med. Bias	MAD	rp(.05)
F* = 2.5															
2SLS(100)		0.007	0.001	0.005	0.058		0.016	0.014	0.014	0.552		0.029	0.028	0.028	0.994
LIML(100)		0.015	0.001	0.009	0.052		0.013	0.000	0.009	0.034		0.012	0.000	0.008	0.044
FULL(100)		0.015	0.001	0.009	0.052		0.013	0.000	0.009	0.034		0.012	0.000	0.008	0.044
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
F* = 10															
2SLS(100)		0.009	0.000	0.006	0.052		0.015	0.011	0.012	0.262		0.022	0.020	0.020	0.656
LIML(100)		0.011	0.000	0.007	0.052		0.011	0.000	0.007	0.066		0.011	-0.001	0.007	0.058
FULL(100)		0.011	0.000	0.007	0.052		0.011	0.000	0.007	0.066		0.011	-0.001	0.007	0.054
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	1	0.010	0.000	0.007	0.042	0	0.011	0.002	0.007	0.054	1	0.011	0.003	0.007	0.070
Post-LASSO-F	1	0.010	0.000	0.006	0.052	0	0.010	0.003	0.007	0.066	1	0.011	0.003	0.007	0.088
F* = 40															
2SLS(100)		0.009	0.000	0.006	0.032		0.011	0.006	0.008	0.108		0.015	0.012	0.012	0.248
LIML(100)		0.009	0.000	0.006	0.032		0.010	0.000	0.007	0.066		0.009	0.000	0.006	0.046
FULL(100)		0.009	0.000	0.006	0.032		0.010	0.000	0.007	0.064		0.009	0.000	0.006	0.042
LASSO	497	0.005	-0.001	0.004	0.000	500	*	*	*	0.000	497	0.014	-0.006	0.009	0.000
Post-LASSO	497	0.010	-0.001	0.007	0.000	500	*	*	*	0.000	497	0.012	-0.005	0.008	0.000
LASSO-F	0	0.010	0.000	0.006	0.044	0	0.010	0.001	0.007	0.052	0	0.010	0.002	0.007	0.046
Post-LASSO-F	0	0.009	0.000	0.006	0.038	0	0.010	0.002	0.007	0.058	0	0.010	0.002	0.007	0.056
F* = 160															
2SLS(100)		0.010	0.000	0.007	0.060		0.010	0.003	0.007	0.076		0.012	0.007	0.009	0.128
LIML(100)		0.010	0.000	0.007	0.064		0.010	0.000	0.007	0.044		0.010	0.000	0.007	0.046
FULL(100)		0.010	0.000	0.007	0.064		0.010	0.000	0.007	0.044		0.010	0.000	0.007	0.048
LASSO	349	0.011	-0.001	0.008	0.014	358	0.010	0.003	0.007	0.004	351	0.012	0.004	0.007	0.024
Post-LASSO	349	0.010	-0.001	0.007	0.016	358	0.010	0.003	0.008	0.006	351	0.011	0.003	0.007	0.024
LASSO-F	0	0.011	0.000	0.007	0.066	0	0.010	0.001	0.007	0.048	0	0.010	0.002	0.007	0.056
Post-LASSO-F	0	0.010	0.000	0.007	0.066	0	0.010	0.001	0.007	0.042	0	0.010	0.002	0.007	0.064

Note: Results are based on 500 simulation replications and 100 instruments. The first 50 first-stage coefficients were set equal to one and the remaining 50 to zero in this design. Corr( $\epsilon, y$ ) is the correlation between first-stage and structural errors.  $F^*$  measures the strength of the instruments as outlined in the text. 2SLS(100), LIML(100), and FULL(100) are respectively the 2SLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.

Table 13: 2SLS Simulation Results. Cut-Off Design,  $S = 100$ ,  $N = 100$ 

Estimator	Select 0	Corr( $e, y$ ) = 0				Corr( $e, y$ ) = .3				Corr( $e, y$ ) = .6					
		RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)
F* = 2.5															
2SLS(100)		0.013	0.000	0.009	0.068		0.024	0.021	0.021	0.378		0.043	0.041	0.041	0.916
LIML(100)		6.463	0.006	0.065	0.012		2.172	0.008	0.061	0.076		0.697	0.017	0.060	0.145
FULL(100)		0.950	0.006	0.065	0.012		0.701	0.008	0.061	0.076		0.555	0.017	0.060	0.145
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
F* = 10															
2SLS(100)		0.014	0.000	0.008	0.054		0.019	0.012	0.013	0.152		0.030	0.027	0.027	0.486
LIML(100)		1.387	0.002	0.044	0.026		2.774	0.001	0.044	0.040		1.250	0.007	0.046	0.074
FULL(100)		1.171	0.002	0.044	0.026		0.539	0.001	0.044	0.040		1.131	0.007	0.046	0.074
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
F* = 40															
2SLS(100)		0.016	0.000	0.010	0.074		0.017	0.007	0.010	0.088		0.021	0.014	0.015	0.176
LIML(100)		0.203	0.002	0.026	0.034		1.345	0.005	0.027	0.022		0.803	0.002	0.023	0.050
FULL(100)		0.202	0.002	0.026	0.034		1.139	0.005	0.027	0.022		0.782	0.002	0.023	0.050
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
F* = 160															
2SLS(100)		0.015	0.000	0.010	0.054		0.015	0.004	0.011	0.054		0.016	0.007	0.011	0.086
LIML(100)		0.376	0.001	0.019	0.028		0.221	0.000	0.019	0.010		0.277	-0.001	0.020	0.030
FULL(100)		0.376	0.001	0.019	0.028		0.221	0.000	0.019	0.010		0.277	-0.001	0.020	0.030
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000

Note: Results are based on 500 simulation replications and 100 instruments. All first-stage coefficients were set equal to one in this design. Corr( $e, y$ ) is the correlation between first-stage and structural errors.  $F^*$  measures the strength of the instruments as outlined in the text. 2SLS(100), LIML(100), and FULL(100) are respectively the 2SLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.

Table 14: ZSLS Simulation Results. Cut-Off Design,  $S = 100$ ,  $N = 250$ 

Estimator	Select 0	Corr( $e, y$ ) = 0					Corr( $e, y$ ) = .3					Corr( $e, y$ ) = .6				
		RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)	Select 0	RMSE	Med. Bias	MAD	rp(.05)	Select 0
ZSLS(100)		0.008	0.000	0.005	0.050		0.015	0.013	0.013	0.390		0.027	0.026	0.026	0.926	
LIML(100)		0.013	0.000	0.008	0.048		0.011	0.000	0.007	0.034		0.012	0.001	0.008	0.042	
FULL(100)		0.013	0.000	0.008	0.046		0.011	0.000	0.007	0.034		0.012	0.001	0.008	0.044	
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
Post-LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
$F^* = 10$																
ZSLS(100)		0.009	0.001	0.006	0.068		0.012	0.009	0.009	0.158		0.019	0.016	0.016	0.456	
LIML(100)		0.011	0.001	0.007	0.064		0.010	0.001	0.007	0.048		0.010	0.000	0.007	0.056	
FULL(100)		0.011	0.001	0.007	0.064		0.010	0.001	0.007	0.046		0.010	0.001	0.007	0.054	
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
Post-LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
$F^* = 40$																
ZSLS(100)		0.009	0.000	0.007	0.046		0.011	0.005	0.007	0.090		0.013	0.009	0.010	0.150	
LIML(100)		0.010	0.000	0.007	0.044		0.010	0.000	0.007	0.050		0.010	0.000	0.006	0.050	
FULL(100)		0.010	0.000	0.007	0.044		0.010	0.000	0.007	0.050		0.010	0.000	0.006	0.050	
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
LASSO-F	487	0.011	0.003	0.009	0.000	496	0.010	-0.003	0.009	0.000	494	0.008	-0.006	0.007	0.000	
Post-LASSO-F	487	0.010	0.001	0.006	0.002	496	0.007	-0.004	0.008	0.000	494	0.009	-0.008	0.008	0.000	
$F^* = 160$																
ZSLS(100)		0.010	0.000	0.007	0.054		0.010	0.003	0.006	0.080		0.011	0.005	0.007	0.088	
LIML(100)		0.010	0.000	0.007	0.052		0.010	0.000	0.006	0.064		0.010	0.000	0.006	0.058	
FULL(100)		0.010	0.000	0.007	0.052		0.010	0.000	0.006	0.062		0.010	0.000	0.006	0.058	
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000	
LASSO-F	475	0.010	-0.001	0.006	0.000	478	0.016	-0.001	0.009	0.006	477	0.011	0.003	0.009	0.002	
Post-LASSO-F	475	0.009	-0.005	0.007	0.000	478	0.016	-0.002	0.007	0.008	477	0.011	0.003	0.007	0.002	

Note: Results are based on 500 simulation replications and 100 instruments. All first-stage coefficients were set equal to one in this design. Corr( $e, y$ ) is the correlation between first-stage and structural errors.  $F^*$  measures the strength of the instruments as outlined in the text. ZSLS(100), LIML(100), and FULL(100) are respectively the ZSLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.

Table 15: 2SLS Simulation Results. Cut-Off Design,  $S = 100$ ,  $N = 500$ 

Estimator	Select 0	Corr( $e, y$ ) = 0				Select 0	Corr( $e, y$ ) = .3				Select 0	Corr( $e, y$ ) = .6			
		RMSE	Med. Bias	MAD	rp(.05)		RMSE	Med. Bias	MAD	rp(.05)		RMSE	Med. Bias	MAD	rp(.05)
F* = 2.5															
2SLS(100)		0.006	0.000	0.004	0.046		0.011	0.009	0.009	0.396		0.019	0.018	0.018	0.920
LIML(100)		0.008	0.001	0.005	0.048		0.008	0.000	0.006	0.052		0.007	0.000	0.005	0.036
FULL(100)		0.008	0.001	0.005	0.044		0.008	0.000	0.006	0.052		0.007	0.000	0.005	0.040
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO-F	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
F* = 10															
2SLS(100)		0.006	0.000	0.004	0.048		0.009	0.006	0.006	0.180		0.012	0.011	0.011	0.412
LIML(100)		0.007	0.000	0.004	0.048		0.007	0.000	0.005	0.062		0.007	-0.001	0.005	0.050
FULL(100)		0.007	0.000	0.004	0.046		0.007	0.000	0.005	0.062		0.007	-0.001	0.005	0.052
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	340	0.006	0.000	0.004	0.004	325	0.007	0.000	0.004	0.026	316	0.007	0.000	0.004	0.014
Post-LASSO-F	340	0.006	0.000	0.004	0.008	325	0.007	0.000	0.004	0.022	316	0.007	0.001	0.004	0.014
F* = 40															
2SLS(100)		0.006	0.000	0.004	0.038		0.008	0.003	0.006	0.092		0.009	0.006	0.007	0.164
LIML(100)		0.007	0.000	0.004	0.040		0.007	0.000	0.005	0.078		0.007	0.000	0.005	0.048
FULL(100)		0.007	0.000	0.004	0.040		0.007	0.000	0.005	0.078		0.007	0.000	0.005	0.048
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	0	0.007	0.000	0.005	0.036	2	0.007	0.000	0.005	0.070	0	0.007	0.001	0.005	0.060
Post-LASSO-F	0	0.007	0.000	0.005	0.034	2	0.007	0.001	0.005	0.064	0	0.007	0.001	0.005	0.066
F* = 160															
2SLS(100)		0.007	0.000	0.005	0.052		0.007	0.002	0.005	0.060		0.008	0.003	0.005	0.090
LIML(100)		0.007	0.000	0.005	0.052		0.007	0.000	0.005	0.058		0.007	0.000	0.005	0.044
FULL(100)		0.007	0.000	0.005	0.052		0.007	0.000	0.005	0.060		0.007	0.000	0.005	0.044
LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
Post-LASSO	500	*	*	*	0.000	500	*	*	*	0.000	500	*	*	*	0.000
LASSO-F	0	0.007	0.000	0.005	0.048	0	0.007	0.000	0.005	0.050	0	0.007	0.001	0.005	0.056
Post-LASSO-F	0	0.007	0.000	0.005	0.056	0	0.007	0.000	0.005	0.056	0	0.007	0.001	0.005	0.048

Note: Results are based on 500 simulation replications and 100 instruments. All first-stage coefficients were set equal to one in this design. Corr( $e, y$ ) is the correlation between first-stage and structural errors.  $F^*$  measures the strength of the instruments as outlined in the text. 2SLS(100), LIML(100), and FULL(100) are respectively the 2SLS, LIML, and Fuller(1) estimator using all 100 potential instruments. Many-instrument robust standard errors are computed for LIML(100) and FULL(100) to obtain testing rejection frequencies. LASSO and Post-LASSO respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 100 instruments. LASSO-F and Post-LASSO-F respectively correspond to IV using LASSO or Post-LASSO with the refined data-driven penalty to select among the 120 instruments formed by augmenting the original 100 instruments with the first 20 principal components. We report root-mean-square-error (RMSE), median bias (Med. Bias), mean absolute deviation (MAD), and rejection frequency for 5% level tests (rp(.05)). "Select 0" is the number of cases in which LASSO chose no instruments. In these cases, RMSE, Med. Bias, and MAD use only the replications where LASSO selects a non-empty set of instruments, and we set the confidence interval equal to  $(-\infty, \infty)$  and thus fail to reject.